Using Remote Sensing and Machine Learning to evaluate the interaction between agricultural expansion and the environment: A study of the Brazilian Cerrado

by

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B.S., Sichuan Normal University, 2009
M.S., Wuhan University, 2011

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Geography and Geospatial Sciences
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2021

Abstract

Global population growth has increased the demand for food, and many countries have answered this problem by expanding agricultural lands. Brazil stands out as one of the world's fastest growing agricultural development zones, especially in the Brazilian savanna, which has been transformed into an important world breadbasket. Meanwhile, the region is also one of the world's biodiversity hotspots. Continuous agricultural expansion including the new agricultural frontier (Matopiba region, which is in the northern part of the Cerrado) has affected the natural environment and ecosystems in the region. Although many studies have used different methods to estimate the interaction between agricultural expansion and the environment, the performance of combining remote sensing and machine learning is still unclear. The main goal of this dissertation is to examine the interaction between agricultural expansion and the environment using remote sensing and machine learning from aspects of pollinator, crops, vulnerability, and fire activity.

In the following chapters, the interaction between agricultural expansion and the environment will be investigated using a combination of model approaches, remote sensing, GIScience, machine learning, deep learning, and data mining. Chapter 2 presents a spatial distribution of selected bee species richness and soybean production at a regional scale. The findings indicate that higher bee species richness and higher soybean production are in the southern Cerrado, and the environment has a stronger impact on bee species richness than soybean production. Additionally, the analysis of the interaction of bee species richness and soybean production reveals that their relationship is not a linear one. Chapter 3 develops an indicator system to estimate environmental vulnerability in the entire Cerrado. The main finding is that areas of high environmental vulnerability are in the southern Cerrado. Additionally, mined

historical Twitter results reveal that social media data is a promising data set for environmental vulnerability assessment. Chapter 4 creates a novel deep learning model (Conv-LSTM) to classify two agricultural expansion sites in the Matopiba region over time and estimates the correlation between land use types and burned areas in September (the last month of the dry season) using classification results and the MODIS products. The findings determine that the proposed model can classify different land structure areas at coarse spatial resolution. Additionally, the overlay analysis with burned areas indicates that fire activities easily occurred in the grasslands in Site A and the forestlands in Site B. The results also claim that fire activities more readily occurred at the edge of cropland areas, which suggest that fire activities are still a common way to expand agriculture in this region.

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Acknowledgements

I am extremely grateful to my loving parents because I missed so many moments. Many thanks! Thank you for supporting me during these five years. I cannot finish this hard journey without your infinite support.

I want to first express my deep respect for my major advisor, Dr. Marcellus M. Caldas, who is a kind and strict advisor. During these five years working with him, I learned how to describe my ideas and how to critically write an academic paper. Thank you for your guidance and support. The most important thing I learned from him is how to self-criticize my own work and effectively improve my writing.

It is difficult to separate my supervisory committee members from this meaningful journey. To Dr. William H. Hsu, a professor in the Computer Science Department. I thank him for providing the introduction of machine learning knowledge to me. Working with him expanded the scope of my research and enlightened me to think about problems using a machine learning perspective. I also want to thank him for giving me access to his lab and assigning to me one of his doctoral students to help me solve problems. I learned a lot about programming from these peers.

I would like to express my sincere gratitude to Dr. Douglas Goodin, who is a wise professor in the field of remote sensing. I learned a lot from him including how to improve my academic writing skills and how to solve problems using remote sensing imagery. More importantly, I want to thank him for providing so many interesting ideas.

My sincere thanks also go to Dr. Paulo de Marco Jr, a professor from the Federal University of Goias in Brazil. Working with him taught me how to connect ecological phenomena with geography, or more accurately “ecological landscapes”. I thank you for helping

me find a place to stay when I travelled to Brazil in the 2018 and 2019 summers. I also want to thank you for allowing me to stay in your lab to work with other peers. Although I do not know how to speak Portuguese, you asked students who know English to work with me. There are many gaps in different majors, and I am happy to know there are some potential connections between ecology and geography.

My studies also received supports from the Department of Geography and Geospatial Sciences, College of Arts & Sciences, and Graduate Student Council at Kansas State University. The department generously offered me the funds that supported my travel to Goiania (Brazil) over two summers and provided me with funds to attend the annual conference of the Association of American Geographer (AAG), which is an international conference where I presented my work in front of peers. The College of Arts & Sciences also funded my travel to the AAG meetings every year through the student research travel award. I also want to thank the Graduate Student Council for the funds granted me during these four years.

I am grateful for the people I met during my PhD program. Starting from the professors in the Department of Geography and Geospatial Sciences at Kansas State University, where they gave me with great help with my research. Dr. Hutchinson, in particular, helped me out with so many GIS problems. Dr. Nelson, I appreciate the many hours that we discussed environmental vulnerability problems. Huichen, Yang, who is one of Dr. Hsu's doctoral students, answered many questions about programming for me.

Finally, I want to especially thank Daniel Paiva Silva, who is a former student of Dr. Paulo de Marco Jr. He gave me a lot of help with the Chapter 2, his feedback always setting me on the right path.

Dedication

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Preface

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Chapter 1 - Introduction

1.1 Research Goals and Objectives

Global population is growing and as a consequence the demand for food has increased (Ezeh et al., 2012; Godfray et al., 2010). Many countries have answered this problem by expanding cultivated lands. Brazil stands out as one of the world's fastest growing agricultural development zones, especially in the Brazilian Savanna (Rada, 2013; Sano et al., 2019). The Brazilian Savanna or the Cerrado, has been transformed into an important world breadbasket, and in its northern region there is a new agricultural frontier called Matopiba, which includes parts of Maranhao, Tocantins, Piaui and Bahia states (Araújo et al., 2019). However, the Cerrado is also one of the world's biodiversity hotspots (Beuchle et al., 2015a; Klink and Machado, 2005) and continuous agricultural expansion in this area has affected environmental systems (Barretto et al., 2013; de Oliveira Silva et al., 2015; Dias et al., 2016; Hunke et al., 2015b).

Many scholars have presented alternatives to solve this problem such as extensification and intensification land use responses (Barretto et al., 2013; Dias et al., 2016; Lambin and Meyfroidt, 2010). Some studies also analyzed particular environmental problems such as soil erosion and land degradation at the local scale using census data, remote sensing images, regression models or some combination of them (Caldas et al., 2017; Grecchi et al., 2014; Leite et al., 2012; David Tilman et al., 2011). However, combining remote sensing and machine learning to estimate the interaction between agricultural expansion and the environment is still unclear. In this dissertation, I will choose pollinator, crops, vulnerability, and fire activity to estimate the interaction between agricultural expansion and environment using remote sensing imagery, machine learning techniques and social media data. Particularly, I will:

Objective 1: Understand the spatial distribution between pollinator and soybean production using a species distribution model and a crop simulation model;

Objective 2: Estimate environmental vulnerability in the Cerrado using remote sensing, machine learning and Twitter data;

Objective 3: Develop a deep learning model to map agricultural areas in the Matopiba region and estimate its correlation with burned areas.

1.2 Motivation

The world population will continue to grow, and it is likely to reach around 9 billion by the middle of this century. Meanwhile, the demand for food is rising and may continue for several decades (Godfray et al., 2010). Until 2011 it was estimated that agricultural land could occupy an additional 200-300 million hectares globally (Barretto et al., 2013; Brown, 2016; Chaplin-kramer et al., 2015; David Tilman et al., 2011). Among the countries, Brazil became a popular example about agricultural expansion because of its miracle agricultural achievement in the Cerrado, the Brazilian Savanna (Lambin and Meyfroidt, 2010; Martinelli et al., 2010; Rada, 2013; Spera et al., 2016a).

The Brazilian Savanna (the Cerrado) has been transformed into a world breadbasket with a new emphasis on the declared agricultural frontier of Matopiba (a region that includes parts of the states of Maranhao, Tocantins, Piaui and Bahia); more than 80% of the region is in the Cerrado, which accounts for almost 10% of the country's total grain production (Araújo et al., 2019; Henrique and Barros, 2019; Salvador and de Brito, 2018). The Cerrado also has the richest flora among the world's savannas (>7000 species) and the highest species richness of birds, fish, reptiles, amphibians, and insects (Klink and Machado, 2005). With continuous agricultural expansion, this area has turned into one of the world's biodiversity hotspots (Beuchle et al., 2015a; Ratter et al., 1997).

There are two different ways to consider agricultural expansion. On the one hand, land use intensification means increasing productivity per unit of area without increasing its area (Barretto et al., 2013; Chaplin-kramer et al., 2015; Dias et al., 2016; Spera, 2017a). Under current environmental conditions, many scholars argue that sustainable intensification could achieve food security and minimize negative environmental impacts (Burney et al., 2010; Loos et al., 2014; David Tilman et al., 2011; Tscharntke et al., 2012a). For example, intensification can improve agricultural production while conserving the remainder of the Cerrado (Spera, 2017a). Land use extensification, on the other hand, consists of increasing production by expanding agriculture area (Caldas et al., 2017; Lambin et al., 2003; Lambin and Meyfroidt, 2010). However, this type of agriculture activity has been one of the main drivers of deforestation, a major source of carbon emission and biodiversity loss (Dias et al., 2016). Nevertheless, both agricultural expansion modes can directly and indirectly affect environments (Lahsen et al., 2016).

Many studies have estimated the impact of agricultural expansion on environments, and the majority of the research has analyzed this problem through census data, regression models, remote sensing analysis or a combination of these approaches (Barretto et al., 2013; Grecchi et al., 2014; Jepson, 2005; Leite et al., 2012; Schwieder et al., 2016). However, few studies focused on combining remote sensing and machine learning techniques to examine the effects agriculture expansion on environments.

To estimate it, there are many different approaches. For example, Imbach et al. (2017b) used a species distribution model to estimate the influence of climate change on bees, which are an important pollinator for coffees. Other studies used different species to examine species richness and environmental changes using a modeling approach (Calabrese et al., 2014; Distler et al., 2015; Guisan and Rahbek, 2011). Moreover, some of the research also applied crop simulation modeling to estimate crop production associated with the environment (Curnel et al., 2011; Huang et al., 2016a; Jin et al., 2018). However, combining a species distribution model and a crop simulation model to estimate the spatial distribution of pollinators and crop at a regional scale is still unclear in the Cerrado biome.

In addition, agricultural expansion has caused soil erosion, natural vegetation loss, and land degradation, which make the local environment vulnerable for the provision of livelihood (EPA, 2019; Lahsen et al., 2016). Estimating environmental vulnerability in the Cerrado caused by agricultural expansion can help us understand the internal construction of the environmental system. Among published methods, the most common one is to establish a variables system and calculate the value of environmental vulnerability. However, fewer studies have taken into consideration machine learning algorithms and social media data sets. Recently, machine learning has been broadly used in many different fields because of its ability to deal with nonlinear relationships between features (Kotsiantis et al., 2006; Luo et al., 2019). Many studies have proven that machine learning technique algorithm is a robust method and can improve the performance of results (Mountrakis et al., 2011; Shao and Lunetta, 2012; Were et al., 2015; C. Zhang et al., 2019). Meanwhile, in recent years, social media has emerged as a popular way to describe people's feelings or perspectives about a particular event (Batrinca and Treleaven, 2014; Gundecha and Liu, 2012; Stieglitz et al., 2018). Mining useful information from social media has become a potential resource to improve the management of crisis situations, and some studies have extracted useful information from social media to analyze floods and other disasters, or to map disaster areas (Cervone et al., 2016; Rosser et al., 2017; Wang and Ye, 2018). The performance of integrating machine learning and social media data to estimate environmental vulnerability in the Cerrado still needs to be tested.

Meanwhile, the new agricultural frontier (Matopiba region) in the northern Cerrado is defined as a region dominated by natural vegetation that started to face intensive agricultural-related land occupation (Araújo et al., 2019). In this region, infrastructure is poor, land prices are cheap, and the climate and topographic relief are favorable for agriculture (MAPA, 2019). With continuous agricultural expansion, it is important for us to identify each type of land use and estimate its correlation with burned areas, which is one potential environmental problem. Among different alternatives, deep learning methods caught the attention of scholars after Lecun et al., (2015) published a deep learning review paper in the journal *Nature*. It has been introduced into the geographic field for analysis of the consequences of human activity on the environment (C. Zhang et al., 2019; L. Zhang et al., 2017; Zhu et al., 2017). Many studies have applied deep learning models to classify remote sensing images, and their results indicate that its performance is much better than transitional machine learning methods (Maggiori et al., 2016; Paoletti et al., 2018; Sharma et al., 2017). In the Matopiba region, the dominate land use types are forestland and grassland, but continuous agricultural expansion has converted more than 50% of the natural vegetation into crops (Filho and Costa, 2016). Thus, mapping vegetation areas became a necessary step toward understanding the interaction between agricultural expansion and the environment. Although the deep learning model has many applications for classifying remote sensing images (Donahue et al., 2017; Ndikumana et al., 2018; Shi et al., 2015), creating a reliable deep learning model to classify time series remote sensing images is still unclear. In addition, overlaying land use maps and burned areas can help us understand the internal relationship between agricultural expansion and environment.

1.3 Study area description

The Brazilian Cerrado is the second largest ecoregion in Brazil, occupying the central plateau of the country and representing about 23% of the land surface of the country (Ratter et al., 1997) (Figure 1.1). It has two seasons: a wet season starting in October and lasting about six to seven months, and the dry season starting in April. The amount of rain is about 800–2000 mm/year, and the average annual temperature is 18–28 °C (Klink and Machado, 2005). Because of its unique geographic position, the typical Cerrado vegetation ranges from closed or open canopy deciduous and semi-deciduous forest with shrub to natural grassland (Beuchle et al., 2015a; Spera, 2017a). During three decades of development, the Cerrado has become the leading producer of major export crops, and it accounted for the majority of Brazil's planted area in soybean (61%), maize (61%), and cotton (99%) (Dickie et al., 2016; Filho and Costa, 2016; Rada, 2013). The Matopiba region (about 73 million ha), located in the northern part of the Cerrado, is an acronym formed from the first letters of the four states located mostly in the Cerrado (Maranhao, Tocantins, Piauiand and Bahia). It has emerged as an important agricultural frontier over the past three decades, and this region now produces around 10% of the nation's crops and is a critical driver of the expansion in soybean and maize production (Filho and Costa, 2016). From 2000 to 2014, soybean production increased from 1 million to 3.4 million hectares in this area (Araújo et al., 2019; Horvat et al., 2015; USDA, 2014). Agriculture expansion has become the dominant land use and land cover change in the Cerrado and it has caused many environmental problems such as biodiversity decline, carbon emissions, soil erosion, water pollution, and land degradation (Grecchi et al., 2014; Hunke et al., 2015a; Ratter et al., 1997).

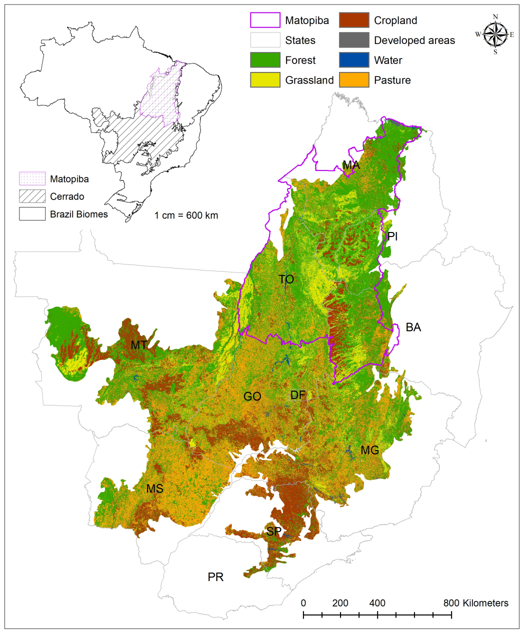

Figure 1.1 The geographical location of the study area and spatial distribution of land use and land cover types for 2014. The abbreviations of the Brazilian states' names are as follows: BA: Bahia; DF: Distrito Federal; GO: Goiás; MA: Maranhão; MG: Minas Gerais; MT: Mato Grosso; MS: Mato Grosso do Sul; PI: Piauí; PR: Paraná; SP: São Paulo; TO: Tocantins.

1.4 Conceptual framework

The main goal of this dissertation to combine remote sensing and machine learning to study the interaction between agricultural expansion and the environment in the Cerrado. The idea of this dissertation starts from agricultural expansion in the Cerrado. It can indirectly or directly interplay with environmental factors such as affecting the pollinator's habitat and crop production. Furthermore, agricultural expansion could be related to fire activities during the dry season and it could also cause environmental vulnerability (Grecchi et al., 2014; Hunke et al., 2015b; Martinelli et al., 2010) (Figure 1.2).

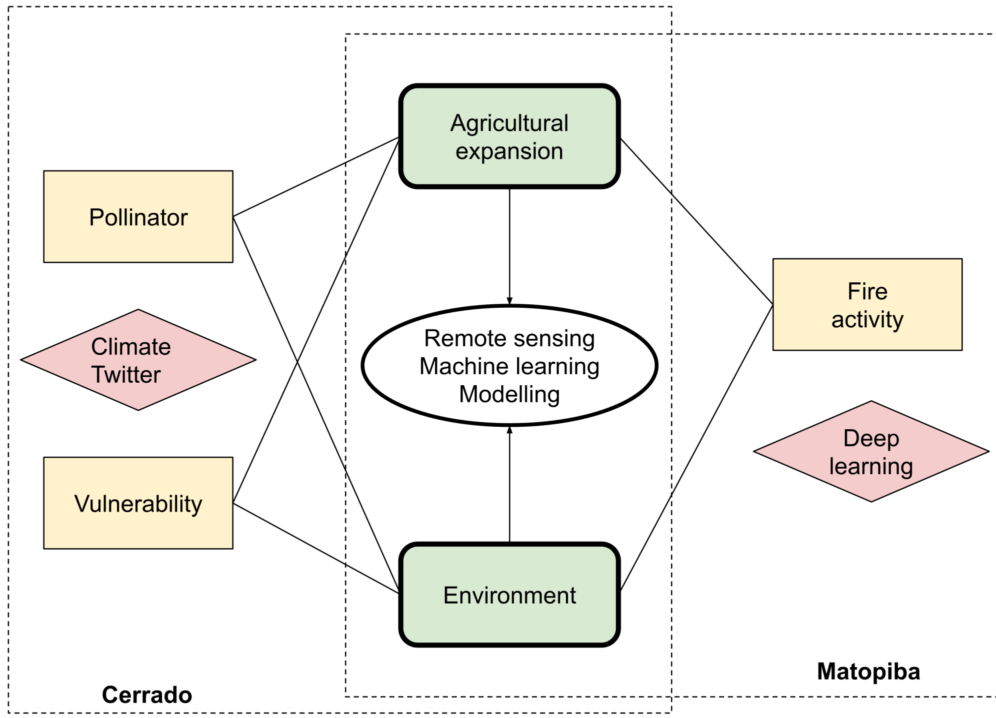

Figure 1.2 The framework of the dissertation. The two green boxes are the main problem. The three yellow boxes are associated with the three chapters. The ellipse shows the main methods in this dissertation.

The Cerrado region is known globally for its biodiversity-rich savanna, which has approximately 160,000 species of fungi, flora, and fauna (Klink and Machado, 2005; Schwieder et al., 2016). However, with the development of agricultural technology and government encouragement, this region has become a biodiversity hotspot and main agricultural zone in Brazil. The first concern about developing agriculture is the influence on species' habitat, and many species are pollinators, which can provide pollination service to improve crop productivity (Aizen et al., 2009, 2019; Hoehn et al., 2008a). Some studies have concluded that climate change and agricultural expansion have reduced the number of pollinators (Elias et al., 2017; Imbach et al., 2017b). In my dissertation, I will expand on these ideas to look into the spatial distribution of pollinator richness and crop production associated with environment variables during the study period.

It is noticeable that agricultural expansion affects not only biodiversity; many studies also show that agricultural expansion can cause soil erosion and land degradation problems (Fuchs et al., 2012; Hunke et al., 2015a; Merten and Minella, 2013), which increase the risk of environmental vulnerability. Facing all these existing or potential risks, it is necessary to estimate environmental vulnerability. Climate change is one of the important factors in environmental systems, and has been used in many environmental research projects (Birkmann et al., 2015; O'Brien et al., 2004; Scarano and Ceotto, 2015). As shown in the Figure 1.2, I will examine environmental vulnerability in the entire Cerrado region by collecting multidimensional indicators.

As a new agricultural frontier in Brazil, the Matopiba region has recently caught the attention of scholars (Araújo et al., 2019; Horvat et al., 2015a). The reason I want to focus on this region is that more than 90% of the region is located in the northern Cerrado, and it is experiencing agricultural expansion because of the cheap land price and government encouragement (Araújo et al., 2019). As one of the great savanna regions of the world, fire activities are also one of the common phenomena during the dry season (de Araújo et al., 2012; Pivello, 2011). It can reduce the amount of biomass present on the landscape and control wild flora and fauna, which can improve the adaptability of the species (Dubinin et al., 2010; Lizundia-Loiola et al., 2020). However, fire activities could also affect the environment by increasing air pollution and disturbing the carbon balance (Beringer et al., 2007; Ravindra et al., 2019; Sun et al., 2016). Some research also pointed out how fire activity is one common way to expand agriculture in this region (de Araújo et al., 2012). To take a closer look at it, in my dissertation I am going to choose two agricultural expansion areas in this region to classify land use types using the deep learning model. Then I will estimate the correlation with burned areas using classification results.

1.5 The outline of the dissertation

My dissertation is organized into three manuscript chapters, corresponding to the three objectives outlined above.

The first manuscript chapter (Chapter 2) uses model approaches to estimate the spatial distribution of pollinators and crops and analyzes their relationship during the 2000 to 2015 period. Among pollinators, I will select 16 bee species with two subgroups. The first group is native species, which are the most common ones to visit local plants, and the second group is a species that visits soybeans. To estimate their spatial distribution, I will use a species distribution model, which is a robust method to predict species distribution. To easily address this problem, I will use the stacked species distribution model (SSDM) to stack the distribution of all single species to generate richness maps in 2000–2008 and 2008–2015 periods. Meanwhile, I will use the common cultivar of soybeans in the Cerrado to simulate and calculate soybean production for selected years. The potential relationship between bee species richness and soybean production will be examined, which will provide a fundamental step toward estimating pollinator, crop, and environment in the Cerrado at a regional scale.

The second manuscript chapter (Chapter 3) estimates environmental vulnerability in the Cerrado using a machine learning algorithm and Twitter data. In this chapter, 11 environmental vulnerability indicators will be created though understanding the definition of vulnerability from the Intergovernmental Panel on Climate Change (IPCC). Then I will use an Autoencoder algorithm to generate optimized features and apply the Ideal Place method (Mishra et al., 2017; Wei et al., 2020) to estimate environmental vulnerability for the years 2011 and 2016. To validate the result, I will also mine historical Twitter data for these two years and overlay with the information with the modeled result. This chapter demonstrates the performance of machine learning algorithms used in the environmental field, and social media data could become a promising data source in the environmental assessment field.

In Chapter 2 and Chapter 3, I investigate the interaction between agricultural expansion and environment for the entire Cerrado. I choose the one environmental composite in Chapter 2 to understand the interaction between soybean, pollinator and environment. However, in Chapter 3, I estimate the environmental influence from a boarder perspective. The following chapter (Chapter 4) will focus on the Matopiba region, more than 80% of which is located in the northern part of the Cerrado; it is the new agricultural frontier in Brazil (Araújo et al., 2019).

It investigates the performance of classifying land use and land cover using a created deep learning model and analyzes the correlation between burned areas and different land use types. Considering the computer capability limitation, I will choose just two sites in the Matopiba region for 2012 and choose September as my study time because fire activities in this month are more than other months. First, I will create a deep learning model (Conv-LSTM) by combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) to classify these two sites and validate my result using an existing data set. Then I will overlay classification results and burned area maps acquired from MCD64A1 MODSI product to estimate their internal relationship.

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Chapter 2 - Bee species richness, soybean production and environment

Abstract

Under current environmental conditions, the spatial distribution of crop production and pollinator richness has been affected by many factors. Estimating their spatial distribution can provide useful information for managing agriculture activity and maintaining a health ecosystem. In this study, we collected environmental variables from remote sensing images and used a stacked species distribution model to predict bee species richness, and a crop simulation model to simulate soybean production at regional scale in the Cerrado in the period 2000-2015. We also analyzed the potential relationship between bee species richness and soybean production using the results from the model. The results showed that from 2000 to 2015, higher bee species richness and higher soybean production were in the southern Cerrado, especially in the states of São Paulo, Minas Gerais, and Goiás. From 2000/08 to 2008/15 period, the bee species richness significantly decreased at the western part of the state of Bahia, the state of Goiás, and the northern region of Minas Gerais, while the soybean production increased in the states of Mato Grosso, Goias, Bahia, and Tocantins. The correlation results of bee species richness and soybean production showed that they did not follow a linear relationship during the study period. Our findings indicate that the modeling methods we proposed are robust for estimating spatial distribution of bee species richness and soybean production in the Cerrado at the regional scale, and climate effects and agricultural expansion are the main factors that affect their spatial distribution and interaction.

2.1 Introduction

Global human population continues to grow and it is likely to reach 9 billion by the middle of the 21th century, thus increasing the supply for food is important (Godfray et al., 2010). Much of the projected global agricultural growth will occur in tropical environments, but tropical environments also compose important ecosystems for the world's biodiversity (Poynton et al., 2007; W. Turner et al., 2003). Unfortunately, many tropical ecosystems are being disturbed by agricultural expansion; approximately one billion hectares of additional land, mostly in developing nations, where tropical ecosystems are located, would be necessary to meet the projected demands for food (D. Tilman et al., 2011; Tilman, 1999). Nevertheless, the ability to increase agricultural production may be mediated by climate change (Ciscar et al., 2018; Wiebe et al., 2015). For example, it was estimated that the EI Ñino Southern Oscillation (ENSO) phenomenon caused between 15% and 35% of global crop production variation in wheat, oilseeds, and coarse grains (Anwar et al., 2013). Some studies also argued that increasing growing season temperature and precipitation had a negative influence on crop yield (Lobell et al., 2012; Lobell and Field, 2007; Zhao et al., 2017).

Climate effects through changing temperature and precipitation patterns also has an obvious effects on the spatial distribution of species, and some studies have concluded that it is one of the biggest ongoing biodiversity threats (Elias et al., 2017; Jeremy T Kerr and Ostrovsky, 2003; Pecl et al., 2017). Under climate change and agricultural expansion, species habitat could be fragmented, interactions could be lost or rewired, and whole biological communities could be affected. For instance, Potts et al. (2010) discussed climate change as one of the factors that caused pollinator decline and very recent evidence has shown that climate change may affect pollination service and crop productions (Elias et al., 2017; Imbach et al., 2017a; Imperatriz-

Fonseca et al., 2017). It is important to notice that one-third of our global food production originates from animal-pollinated, mostly bee-pollinated crops (Hoehn et al., 2008b; Ricketts et al., 2008). Thus, for many agricultural crops, animal pollinators are extremely important by providing a key ecosystem service that improves crop productivity (Hoehn et al., 2008b; Potts et al., 2010; Ricketts et al., 2008). For example, Giannini et al. (2015) pointed out that proper pollination can increase the production and quality of crops in Brazil. They concluded that the total economic contribution of pollinators is approximately 30% (US $ 12 billion) of the total annual agricultural income of the dependent crops (totalizing almost US $ 45 billion) with half of these contributions including the soybean crop (US $ 5.7 billion of pollinators' contribution).

Traditionally, some studies have established empirical models to estimate crop production (Moriondo et al., 2007; Prasad et al., 2006). These works, however, are site specific and focused on the community scale (Ma et al., 2013). Nevertheless, there are other advanced methods used to estimate crop production at the regional scale. For instance, crop simulation models such as the Aquacrop model (Steduto et al., 2009), the DSSAT model (Jones et al., 2003), and the WOrld FOod STudies (WOFOST) model (van Diepen et al., 1989) are increasingly used in recent literature and provide reliable methods to simulate regional to large-scale crops. Generally speaking, these models consider crop environmental conditions during its growing season and many studies have stated that they can achieve a better performance than empirical models such as simply creating the regression relationship between crop information and vegetation index (Jin et al., 2018). Among these models, the WOFOST model is the most robust model to estimate crop yield using remote sensing data (Curnel et al., 2011; J. Huang et al., 2015). Compared with empirical model, the benefit of the crop simulation model is to consider the environmental conditions of the crop during the growing season, and work on the pixel level based on the spatial resolution, which help local land planners to locate high crop production areas and analyze its correlation with productivity corresponding with other biological factors such as pollination services.

The interaction between pollinators and crop is complex. To study the response of pollinators to climate effects and their interaction upon crops, it is crucial to understand the pollinators' spatial distribution. The use of species distribution models (SDMs) has become a standard tool for understanding how environmental factors affect the geographic ranges of species and can be used to predict their response to global changes (Calabrese et al., 2014; Peterson and Soberón, 2012). In addition, many studies have shown that SDMs may perform well in characterizing the natural distributions of species, thus providing useful ecological insights (Elith and Graham, 2009). In general, these models use known species' occurrences data and environmental variables to predict a given species' distribution in areas where there are no known occurrences (Elias et al., 2017; Elith and Leathwick, 2009; Imbach et al., 2017a). As SDMs applications focused on prediction, scholars have sought different methods for modelling, including machine learning algorithms, which outperform other methods to deal with prediction problems (Elith and Graham, 2009; Phillips et al., 1997). Furthermore, most applications require an estimation of species richness in particular areas connecting with environmental changes or analyzing its adaptation. This was achieved by producing stacked SDMs, putting together individual SDMs models to estimate an entire species assemblage (Cord et al., 2014; D'Amen et al., 2015; Guisan and Rahbek, 2011).

Environmental characteristics are one important part in the SDMs and the most common data is the Worldclim dataset (Distler et al., 2015; Elias et al., 2017; Imbach et al., 2017a; Silva et al., 2014). However, there are some limitations related to this dataset (Wisz et al., 2008). For instance, the Worldclim data is obtained only for a limited period of time (1950–2000), which makes it difficult to predict species distribution for more recent times. With the advance of remote sensing techniques, more and more studies started to develop environmental variables using remote sensing data (Jeremy T. Kerr and Ostrovsky, 2003; W. Turner et al., 2003). Therefore, the remote sensing data from National Aeronautics and Space Administration's (NASA) earth observation dataset because of its well documented and continued records have been taken into consideration to estimate the relationship between human activities and environment change over time (W. Turner et al., 2003).

It is important to note that although soybeans are considered a self-pollinating crop, some studies have argued that bees, or more specifically honeybees (Apis mellifera Linnaeus 1758; Apinae: Apini) provide pollination services that can improve soybean production (Chiari et al., 2005; de O. Milfont et al., 2013; Erickson, 2008). Giannini et al. (2015) also concluded that exotic bee species such as A. mellifera and native bee species in Brazil, such as bees from the Meliponini tribe visited the same crops in Brazil, which could include soybean. Nevertheless, the spatial distribution of these bee species richness and soybean production with climate affects and agricultural expansion at regional scale is still unclear. We raised our hypothesis that higher bee species richness could cause higher soybean production in the Brazilian Cerrado. Thus, this study will fill the gap in the literature by using remote sensing data to generate environmental variables to estimate the spatial distribution of bee species richness and soybean production. Specifically, this study will (1) use stacked SDMs to predict bee species richness and the WOFOST model to simulate and calculate soybean production in the Brazilian Cerrado; (2) evaluate the changes of bee pollinators' richness and soybean production over time; and (3) analyze the spatial variability of bee species richness and soybean production based on our results.

2.2 Material and methods

2.2.1 Study area

The Brazilian Cerrado is the second largest biome in Brazil, and has a territory of around two million km^2, which is equivalent to the total size of Germany, France, England, Italy, and Spain combined. The Cerrado has two well-defined seasons with the wet season occurring between October and March, and the dry season from April to September. The average temperature is 23°C, with an average annual rainfall around 1500 mm (Klink and Machado, 2005). The Cerrado has been through enormous agricultural expansion since the mid-20th century, when more than 50% of its natural vegetation was converted into pasture or cropland, thus transforming this region into a biological hotspot for biodiversity conservation (Beuchle et al. 2015; Klink and Machado 2005; Poynton et al. 2007). Soybean has become the main crop in this region with its production representing 90% (15.6 million hectares) of all agricultural production (Filho and Costa, 2016; Gibbs et al., 2015). However, agricultural expansion has affected the habitats for many species including pollinators, which could cause a habitat distribution shift. Among them, bees are the primary ones for most agricultural crops and wild plants in the Brazilian Cerrado (de O. Milfont et al., 2013; Potts et al., 2010).

2.2.2 Data sources and variables

2.2.2.1 Data for stacked SDMs

We collected 16 bee species from these data sources in the period (1970–2015) from literature records, online datasets, such as CRIA's (Centro de Referência em Informação Ambiental) Species Link (http://www.splink.org.br), Global Biodiversity Information Facility (http://www.gbif.org), Inter-American Biodiversity Information Network (https://www.oas.org/en/sedi/dsd/iabin/). These bee species includes A. mellifera and Centris (Heterocentris) analis (Fabricius 1804) (Apinae: Centridini) bees, which are some of the commonest bees that visit soybeans during the flowering season (de O. Milfont et al., 2013). Although soybean is a crop species that does not need visitation by pollinators to produce its beans, it was previously shown that the visiting bees are responsible for yield production increase of soybeans (de O. Milfont et al., 2013). The other 14 bee species are Brazilian native bees, with an important group of pollinators of native plant species [14 Meliponini species: Cephalotrigona capitata Smith 1854, Frieseomelitta varia (Lepeletier 1836), Geotrigona mombuca (Smith 1863), Lestrimelitta limao (Smith 1863), Leurotrigona muelleri (Friese 1900), Melipona marginata Lepeletier 1836, Melipona quadrifasciata anthidioides Lepeletier 1836, Melipona quadrifasciata quadrifasciata Lepeletier 1836, Melipona quinquefasciata Lepeletier 1836, Melipona rufiventris Lepeletier 1836, Nannotrigona testaceicornis (Lepeletier 1836), Paratrigona lineata (Lepeletier 1836), Partamona cupira (Smith 1863), Trigona hyalinata (Lepeletier 1836)]. We used ArcGIS 10.6.1 (ESRI) to clear the repeated point or points that were outside of the study's extent for the period (1970-2000) to create model-required bee's occurrence data. We listed each species' name and unique amount of geographic occurrences in the Table 2.1.

We collected environmental variables from NASA's Goddard Earth Sciences Data and Information Services Center (GES DICS) (with spatial resolution of 25 km*25 km). This dataset provides timely and up-to-date overview of actual climatic conditions over large areas. We selected the monthly data from 1970 to 2015. This dataset represents an improvement in relation to the commonly used data from Worldclim that is restricted to the 1950–2000 time span.

Climatic environmental variables in this study includes annual mean temperature, annual mean precipitation, dry season, and wet season average temperature and precipitation, wind speed, air pressure, and specific humidity. We calculated these variables from the Global Land Data Assimilation System (GLDAS) product (GLDAS_NOAH025_M.2.0 and GLDAS_NOAH025_M.2.1) and from the Tropic Rainfall Measurement Mission product (TRMM_3B43_M).

Table 2.1 The name of the bee's species and number of records

Species' name	Number of unique records
Cephalotrigona capitata	41
Frieseomelitta varia	58
Geotrigona mombuca	68
Lestrimelitta limao	63
Leurotrigona muelleri	83
Melipona marginata marginata	64
Melipona quadrifasciata anthidioides	69
Melipona quadrifasciata quadrifasciata	96
Melipona quinquefasciata	58
Melipona rufiventris	71
Nannotrigona testaceicornis	63
Paratrigona lineata	110
Partamona cupira	57
Trigona hyalinata	105
Apis mellifera	48
Centris analis	39

2.2.2.2 The input data for the WOFOST model

It is important to highlight that there are many different cultivars of soybean in the Brazilian Cerrado. The WOFOST library contains cultivars that are used in the Brazilian Cerrado and, for this study, we selected the one (Soybean_906) that has similar environmental condition as this Brazilian region. To avoid potential error during the model processing, we adjusted temperature from emergence to anthesis and from anthesis to maturity for the selected years. Different crops have different growth length periods and these parameters should be assigned manually in the WOFOST model. Due to the average soybean growth period in the Cerrado, its grow length was chosen from October 15th to March 30th in this study (United States Department of Agricultured, 2014).

To simulate soybean yield, the WOFOST model needs climate variables such as daily minimum and maximum temperature, wind speed, rainfall, radiation, and vapor pressure during the soybean growing season. Daily minimum and maximum temperature and wind speed were directly extracted from GLDAS_NOAH025_3H and GLDAS_CLSM025_D products. We calculated daily radiation and vapor pressure from shortwave radiation flux product and we derived daily air temperature parameters from GLDAS_CLSM025_D product (Alduchov and Eskridge, 1996). Finally, we used the tropic rainfall measurement mission (TRMM_3B42TR_Daily) to get daily precipitation data. In addition to climatic variables, the model inputs require soil parameters, such as soil moisture content at wilting point, field capacity and saturation, hydraulic conductivity of saturated soil, maximum percolation rate of root zone and subsoil, and maximum soil root depth. For the case of the Cerrado, we adjusted soil moisture content parameters based on the literature review (Huang et al., 2016b).

2.3 Model process methods

The continuous agricultural expansion in the Cerrado could negatively affect the habitat availability of bees, causing their species richness to decline by reducing their suitable habitats. Due to the limitation of data sources, we wanted to estimate bee species richness for the period 2000 to 2015. We prepared the geographic distribution of the 16 above-mentioned bee species occurrence data for 1970–2000 to match the time of environmental variables. Then, we used stacked SDMs (SSDMs) to predict bee species richness at two periods (2000/08 and 2008/15). Meanwhile, we used the WOFOST model to simulate soybean production in selected years (2002/03, 2007/08, and 2013/14), which is also within the period of 2000 to 2015.

2.3.1 Stacked SDMs (SSDMs) procedures

The SSDMs are the easiest way to measure the change in the number of species in the landscape. The main process of SSDMs is to project individual species' suitable distribution over the whole landscape that comprises the extent of the study. Then, we convert each single SDM from a continuous suitability map to a presence/absence binary map. Later, we stacked these binary maps to build bee species richness (Calabrese et al., 2014; Distler et al., 2015; Guisan and Rahbek, 2011). Particularly, we chose the SSDM package in R (Schmitt et al., 2017) to process all these mentioned steps due to its convenience and user-friendly interface (Figure 2.1A).

During the process, we just wanted to highlight a couple of important steps. First, the model needs present and absence data of the occurrence data and many studies proved that the presence-absence biotic data in species distribution models tended to perform better than presence-only models (Barbet-Massin et al., 2012; Lavorel et al., 2004; Leroy et al., 2018a; Schmitt et al., 2017). In this study, for each bee species we considered, we created pseudo-absences data of each species with equal number of its presence data randomly within the study area, because Barbet-Massin et al. (2012) concluded that equal number of pseudo-absences with presence data can get a better model result when using the machine learning technique.

Second, SSDM package provides five different methods to generate a distribution model for a given species. In our study, we selected Random Forest (RF) (Breiman et al., 2017), Support Vector Machines (SVM) (GhasemiGol et al., 2009), and Artificial Neural Networks (ANN) (Elith and Leathwick, 2009) since they have a better performance for predicting species distribution when having a limited occurrence dataset (Elith and Graham, 2009).

Third, we chose the ensemble method in the package to generate each species' binary map. In this part, we used the area under the curve (AUC) metric to evaluate the ensemble distributions of each species. The AUC metric is a widely used statistic for assessing the discriminatory capacity of species distribution models (Barbet-Massin et al., 2012; Leroy et al., 2018a). This metric assesses the balance between true positive rate (sensitivity) and false positive rate (100 - specificity). This is a threshold-independent metric that varies from 0 to 1, where values near or equal to 1 represent that the models reached excellent discriminatory power, where 0 indicates poor model fitting. Finally, AUC values around 0.5 represent species predictions no better than a random distribution. To get its binary map, we use sensitivity-specificity equality (SES) to compute the binary map threshold (Schmitt et al., 2017).

2.3.2 WOFOST crop model

There are many crop simulations models available in the literature and we selected the WOFOST model because it can use remote sensing data to simulate crop information at large scales like the Cerrado. The model describes plant growth based on light interception and carbon dioxide assimilation as the growth-driving processes and uses crop phenological development as the growth controlling process (Huang et al., 2016a; Ma et al., 2013). The model provided two scenarios: the potential scenario, where crop growth is just affected by temperature and solar radiation, when no other growth-limiting factors are considered; and the water-limited scenario, where crop growth is just limited by the availability of water (Diepen et al., 1989; Huang et al., 2016a). To accurately simulate crop information, we chose the potential scenario, which can minimize the potential error caused by the different cultivators in the whole Cerrado. The Python Crop Simulation Environment (PCSE), which is the python version of the WOFOST model, was used to simulate soybean yield because of its ability to manipulate input parameters (Figure 2.1 B).

Using adjusted crop file, climate variables, and soil parameters, we simulated average soybean yield at pixel level (25 km by 25 km) in selected years. To calculate soybean production, we also collected the annual soybean cultivated area with spatial resolution of 250 m by 250 m from the years of 2002, 2007, and 2013 (Gibbs et al. 2015). Then, the spatial analysis tool in ArcGIS 10.6.1 was used to count the number of soybean grids (250 m by 250 m) in each 25 km by 25 km pixel and calculate the total soybean production in each pixel (25 km by 25 km) of the selected years.

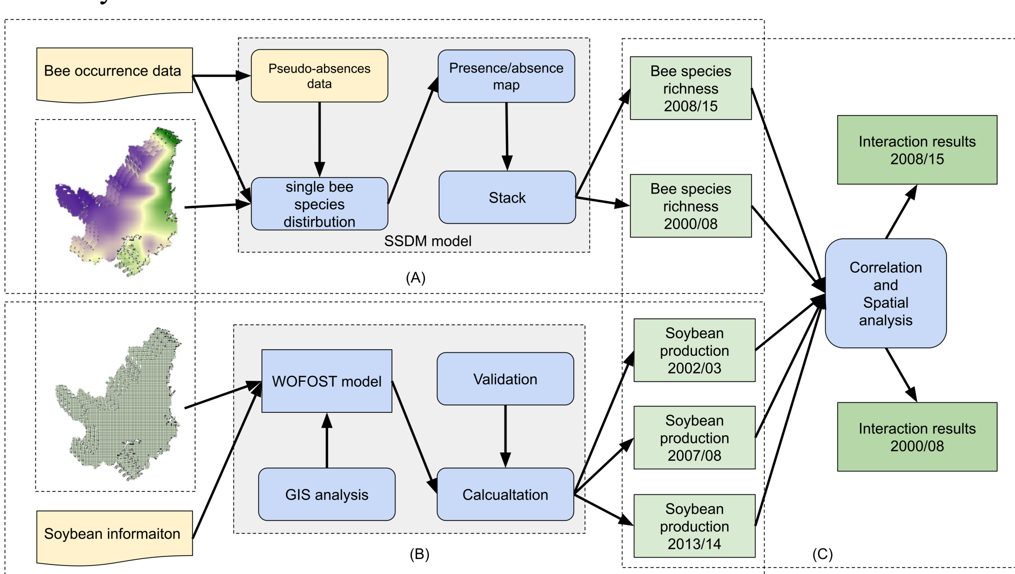


Figure 2.1 The modelling framework illustrating the model process of stacked species distribution model (A) and WOFOST model (B). (C) describes the analysis of interaction between bee species richness and soybean production

2.4 Model validation and results analysis

To validate the results of modeled soybean production, we applied a spatial join tool in ArcGIS 10.6.1. The modeled soybean production at municipality level was calculated by multiplying the average soybean yield and counting the number of soybean grids (250 m by 250 m) in each municipality. Then, we calculated the R-squared (coefficient of determination) of the selected years using modeled soybean production at municipality level and annual soybean production data at municipality level acquired from the Brazilian Institute of Geography and Statistics (IBGE) (Figure 2.1 B).

Since the spatial resolution (25 km by 25 km) of the spatial distribution of bee species richness and soybean production are coarse, even if some bee species do not visit soybean crops during its growing season, there could also be some indirect interaction between them. To analyze the interaction of bee species richness and soybean production, we overlaid these maps using ArcGIS 10.6.1 (Figure 2.1 C). Firstly, we examined the spatial variation of soybean production and bee species richness at the pixel level for the whole Cerrado during these two periods. Second, we calculated the proportion of the soybean cultivated area for each selected year within different bee species richness range.

2.5 Results and Discussion

In this study, we used remote sensing data and two models to estimate bee species richness and soybean production in the Brazilian Cerrado. In the period 2000 to 2015, we obtained the modeled bee species richness (known and potential visitors of soybean) maps for 2000/08 and 2008/15 periods (Figure 2.2) and soybean production in the Brazilian Cerrado at

2002/03, 2007/08, and 2013/14 (Figure 2.4). Generally, our results showed that the high bee species richness and high soybean production is in the southern Cerrado and their spatial distribution may provide us with useful information for analyzing biodiversity and managing soybean expansion in the Cerrado.

2.5.1 Bee species richness result and its change over time

The modeled bee species richness results for the 2000/08 and 2008/15 periods are illustrated in Figure 2. Richness measures the number of species in the landscape, and to analyze the higher or lower of bee species richness, we divided the bee species richness into two parts, where the number of bee species from 1 to 6 is the lower richness, and higher richness is from 7 to 12. We found that the number of bee species higher than 7 was distributed in the southeast part of the Cerrado, more precisely in the states of São Paulo, Minas Gerais, Goiás, and in the western part of the state of Bahia (Figure 2.2 A and B). The possible explanation for such a spatial distribution pattern of bee species richness could be that southern the Cerrado is close to the Atlantic rainforest biome, which has better climate conditions that can provide suitable habitats for bee species. As a result, this model result is due to more occurrence data collected in this region.

These results also showed that the number of bee species less than 5 was on the edge of the Cerrado boundaries (Figure 2.2A and 2.2B). Though the model can create pseudo-absences data to improve the model performance, the insufficiency of bees' occurrence data could cause this result. The quality of occurrence data is one of the most important factors that affects the performance of SDMs, but the sampling bias is a general problem in SDMs, which may cause environmental distribution bias (Barbet-Massin et al., 2012; Kramer-Schadt et al., 2013).

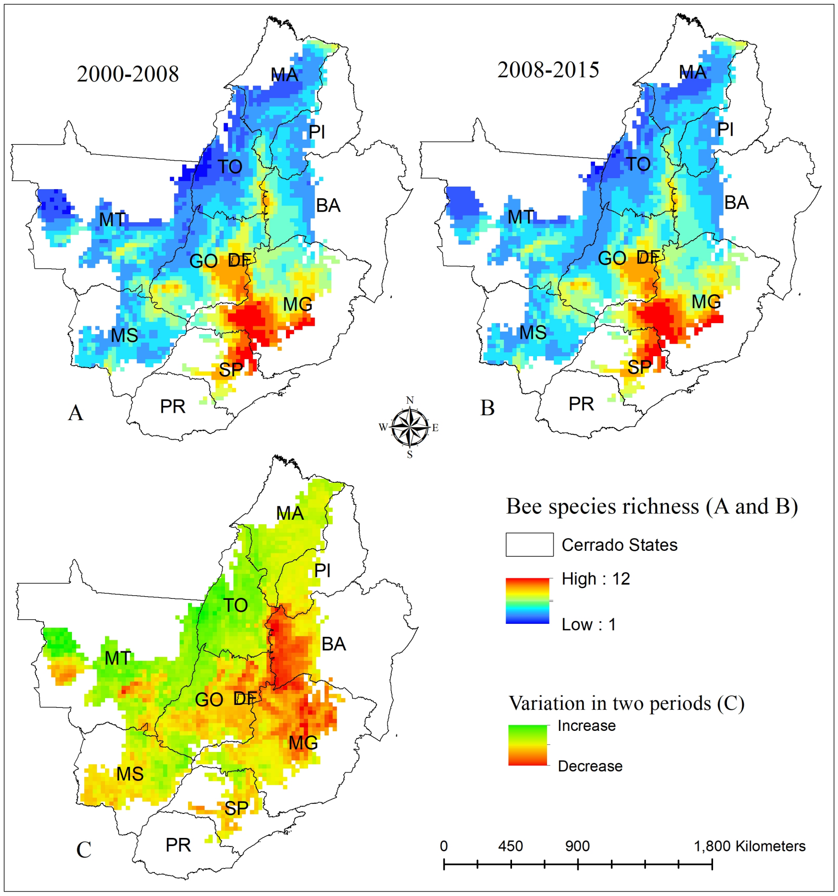


Figure 2.2 Bee species richness in the 2000/08 period (A), the 2008/15 period (B), and the variation of bee species richness in these two periods (C). Higher bee species richness means species equal to or than 7, and lower richness means species equal to or lower than 6. The abbreviations of the Brazilian states' names are as follows: BA: Bahia; DF: Distrito Federal; GO: Goiás; MA: Maranhão; MG: Minas Gerais; MT: Mato Grosso; MS: Mato Grosso do Sul; PI: Piauí; PR: Paraná; SP: São Paulo; TO: Tocantins.

From the 2000/08 to 2008/15 periods, our results found that though the states of Tocantins and Mato Grosso had lower bee species richness, they still slightly increased during these two periods. However, the modeled bee species richness had significantly decreased in the northeastern region of the state of Goiás, the western region of the state of Bahia, and the northern region of the state of Minas Gerais (Figure 2.2C). Climatic variables as one part of the species distribution model have been collected from the Worldclim dataset by many studies and their results are valuable for biodiversity conservation and agricultural management (Elias et al., 2017; Imbach et al., 2017a). The difference from previous studies is that we collected climatic environmental variables from GES DICS dataset to model bee species richness. The result of this study agrees with the study that modeled distribution of bee species are in southern Cerrado using the similar climatic environmental variables from Worldclim dataset (Giannini et al., 2012). One possible explanation of the bee species richness shift could be climate effects and some studies also agree that climate change is one of the main factors causing species shift and decline (Elias et al., 2017; Giannini et al., 2012). Furthermore, during these 15 years, the variation changes of the modeled bee species richness indicates that agricultural expansion in the Cerrado is one of the factors influencing suitable habitat for bees, thus causing either the species shift or populational decline. Particularly, the possible reason of the decrease in the modeled bee species richness in the western region of the state of Bahia is that agricultural expansion in this area is faster than other places in Cerrado (Martinelli et al., 2017).

In addition, the stacked species distribution model used in the study integrated with machine learning algorithms (such as support vector machine, decision tree, and random forest) during the model process. Compared with other statistical methods used in the species distribution model, it has advantages such as yielding better results with limited input data and working with non-linear relationship of data. In this study, we used the ensemble SDM from the Stacked Species Distribution Model (SSDM) to get the bee specie richness in the two periods and the results provided evidence that species distribution model combined with machine learning algorithms is useful for predicting species richness at a regional scale. However, we should keep in the mind that machine learning is not the only suitable method can be used in the species distribution model.

2.5.2 Soybean production result and agricultural expansion

The validation of soybean production showed R-squares of 0.72, 0.6, and 0.58 in the years of 2002/03, 2007/08, and 2013/14, respectively (Figure 2.3). These results indicated that the accuracy of modeled soybean production can exceed 58%, but we noticed that 2013/14 soybean production has the lowest R-square, which means that though we used the same model and adjusted each year's parameters, this year's soybean production result still has the lowest fit to the census data. Furthermore, the results also indicate that soybean cultivars could also affect the accuracy of the modeled results; we only used the same cultivar to model three selected years due to the lack of detailed information on soybean production in the whole Cerrado.

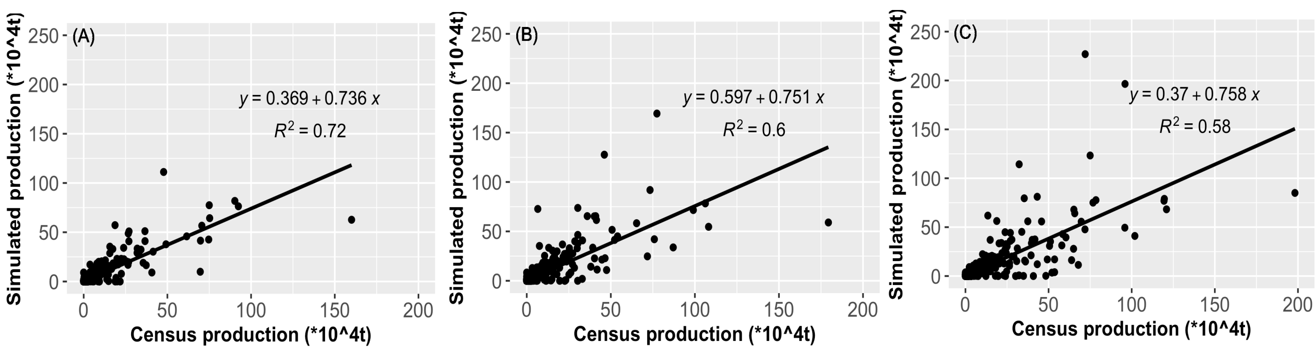


Figure 2.3 Relationship between simulated soybean production and census soybean production 2002/03 (A), 2007/08 (B), and 2013/14 (C). The graphs' X-axes are related to the census soybean production at municipality level (unit: *10^4 ton), while the graphs' Y-axes are the simulated soybean production at municipality level (unit: *10^4 ton). The solid line represents the correlation between the model data and the census data.

The modeled soybean results illustrated the spatial distribution of cultivated soybean areas and their production for selected years in the Cerrado (Figure 2.4). Using remote sensing as one type of data source to simulate crops at the regional scale has improved the simulation results in many studies (Dorigo et al., 2007; J. Huang et al., 2015; Jin et al., 2018; Ma et al., 2013). Our spatial distribution of soybean production results showed that the highest soybean production is in the southern Cerrado, which agrees with Noojipady et al. (2017), who used Moderate Resolution Imaging Spectroradiometer (MODIS) products to estimate the soybean distribution dynamic in the Cerrado. Our results also showed that the proportion of the Cerrado with soybean cultivated areas were 53.64%, 58.55%, and 61.17% for the years of 2002/03, 2007/08, and 2013/14, respectively. Our results indicate that soybean production increased during selected years and the high soybean production distributed in the states of São Paulo, Mato Grosso, Goiás, Minas Gerais, Maranhão, and in the western region of the state of Bahia (Figure 2.4). Traditionally, the states of Mato Grosso, Goias, and Bahia have been recorded as those with the higher soybean production, but our results can identify the particular places having high soybean production in these states, which can provide useful information to local government or farmer to plan agriculture activities effectively.

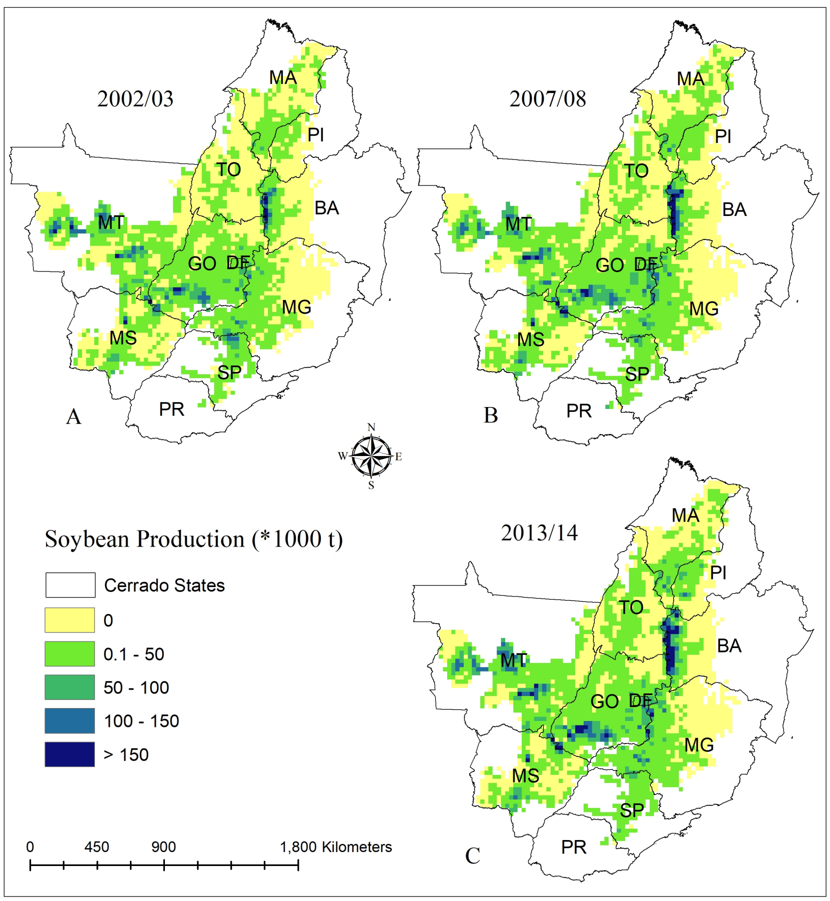


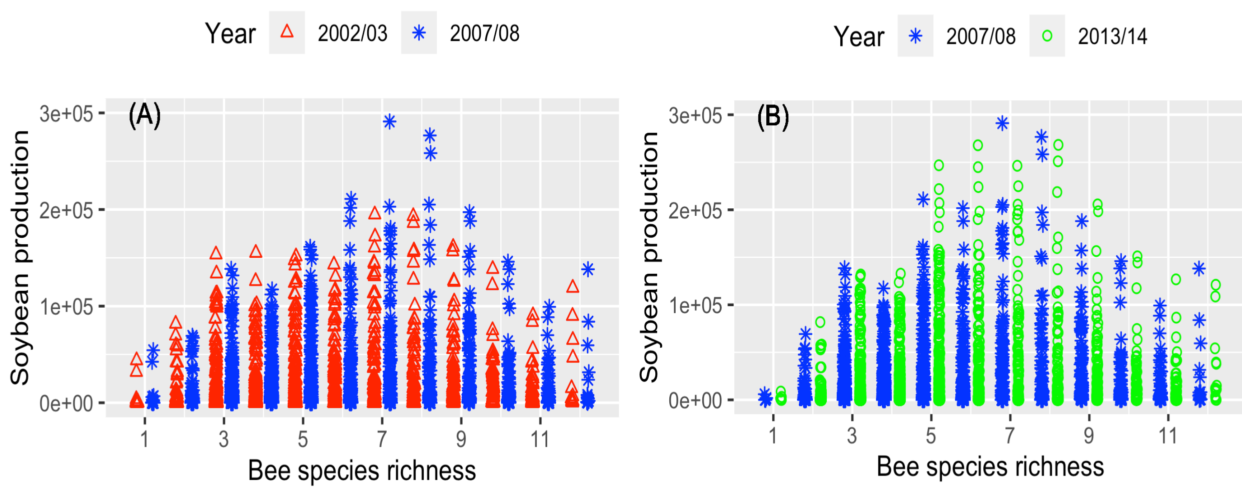
Figure 2.4 Spatial distribution of soybean production for selected years [2002/03 (A), 2007/08 (B), and 2013/14 (C)]with spatial resolution 25 km by 25 km and the unit of each pixel is *1000 ton. The abbreviations of the Brazilian states' names are as follows: BA:

Bahia; DF: Distrito Federal; GO: Goiás; MA: Maranhão; MG: Minas Gerais; MT: Mato Grosso; MS: Mato Grosso do Sul; PI: Piauí; PR: Paraná; SP: São Paulo; TO: Tocantins.

From 2002 to 2008, the soybean cultivated areas expanded 9.16% and from 2008 to 2014, the cultivated areas expanded 4.47%. Meanwhile, the results also showed that soybean production in the Cerrado increased 20.78% from 2002/03 to 2007/08, and 18.31% from 2007/08 to 2013/14. A reasonable explanation for our results is that during these 20 years, enormous agricultural expansion happened in this area and soybeans became a main crop in this region because of its adaptability (Martinelli et al., 2017). The modeled soybean production results state that during these 15 years, soybean production expanded in the Cerrado, and the northern region of the Cerrado has the trend of increasing its production (Figure 2.4). The state of Mato Grosso has currently accounted for one third of soybean production in all of Brazil (Chaplin-kramer et al., 2015), and Horvat, Watanabe, and Yamaguchi (2015) also pointed out that the production of soybeans is rapidly evolving in the state of Tocantins caused by a strong global demand.

2.5.3 Spatial variation of bee species richness and soybean production

To analyze the spatial variation of the modeled bee species richness and soybean production in the Brazilian Cerrado, Figure 2.2 (A and B) and Figure 2.4 (A, B and C) showed that both higher bee species richness and the soybean production were in the Cerrado's southern region. From 2000/08 to 2008/15, both bee species richness and soybean cultivated areas slightly increased along the Cerrado's northern edge. Generally, pollinators can provide pollination service to improve crop production, and we indicate that selected bee species could have some positive influence on soybean in the Cerrado during the study period. Our correlation analysis results showed that overall soybean production in 2007/08 is higher than 2002/03 and 2013/14 is higher than 2007/08 across the whole bee species richness range (Figure 2.5). Previous studies argued that bees can provide pollination service to soybeans to improve its production at the community scale (Aizen et al., 2019; Blettler et al., 2018; de O. Milfont et al., 2013), but our results reveal that selected bee species could have positive influence on soybean production at



regional scale.

Figure 2.5 The correlation between bee species richness and soybean production for two periods. (A) is bee species richness with 2002/03 and 2007/08 soybean production at pixel level in 2000-2008 period; (B) is bee species richness with 2007/08 and 2013/14 soybean production at pixel level in 2008-2015 period

In the current study, we set a very coarse spatial resolution to model bee species richness and soybean production, but we did not contain soybean production as a variable into stacked SDM (SSDM) or bee species richness as a variable into the WOFOST model. Though some selected bee species may not visit the soybean during its growing season, based on the coarse spatial resolution, within each 25km by 25 km pixel, these bee species could also interact with soybean indirectly though pollination of other crops or by being affected by pesticides (Giannini et al., 2015a; Marchioro and Krechemer, 2018). Importantly, the internal relationship between bee species richness and soybean production involves more factors besides climate effects and agricultural expansion, which we have not contained in this study due to the limited dataset. In spite of these drawbacks, our results still provide initial information about the spatial distribution of bee species richness and soybean production in the Cerrado by analyzing the interaction between pollinator and crops production in the Cerrado at the regional scale.

Table 2.2 The percentage of lower and higher bee species richness and soybean cultivated areas by the whole study areas based on the spatial resolution

		Lower (1~6)	Higher (7~12)		Lower (1~6)	Higher (7~12)
Bee species richness (%)	2000–2008	79.61	20.39	2008–2015	80.63	19.37
Soybean cultivated areas (%)	2002/03	37.93	15.69	2007/08	42.88	15.65
	2007/08	42.30	16.24	2013/14	45.10	16.05

Based on our results, we found three relationships between bee species richness and soybean production: (1) soybean production increased as bee species richness increased in regions with lower richness; (2) the peak of soybean production is in the richest areas of bee species, range from 6 to 8; (3) soybean production decreased when bee species richness was higher than 9 (Figure 2.5). From this result, the positive correlation of soybean production and bee species richness in the lower richness range indicates that bee species could have a positive influence on soybean production during the study period. Because the western Cerrado covers more forest, this could provide better habitat for bee species, thus benefiting soybean production. Some studies also agreed that forest fragmentation or crops near rainforest area could receive better pollination services then other places (Ricketts et al., 2008). Secondly, a reliable explanation of the soybean production reaching the peak in the 6 to 8 number of bee species could be that these areas are in the states of Bahia and Goiás, which are important soybean cultivated states in the Cerrado (Martinelli et al., 2017), and the selected bees could provide pollination service to improve its production. Finally, the areas with higher modeled bee species richness do not correspond to those with higher soybean production (Figure 2.2 A and B, Figure 2.4). A possible reason may be the limitation of bee occurrence data. We just collected them from digitized online databases and the literature, so the amount of species we obtained may cause some errors during the modeling process. The other possibility could be that there are other crops or natural vegetation in the areas with the higher bee species richness, and selected bee species could benefit these plants instead of soybean. In addition, during soybean growing season, there are many other factors affecting its production such as irrigation and agricultural technology. The pollinator's availability is just one of them; due to the limitations of our model approaches in this study, we agree that more research is required to deeply understand their relationship.

Furthermore, we calculated the percentage of the soybean cultivated areas in the higher bee species richness and lower bee species richness regions (Table 2.2). Overall, our results showed that 79.61% of the area in the 2000/08 period, and 80.63% of the areas in the 2008/15 period have lower bee species richness (Table 2). Particularly, the results found that soybean planted areas increased from 37.93% (2002/03) to 42.30% (2007/08) in the 2000/08 period, and from 42.88% (2007/08) to 45.10% (2013/14) in the 2008/15 period in the modeled bee species richness from 1 to 6. Meanwhile, in the bee species richness from 7 to 12, the results showed that from 2002/03 to 2007/08 the soybean cultivated areas increased from 15.69% to 16.24% in 2000-2008 period, and from 15.65% to 16.05% in the 2008-2015 period. Our results reveal that in areas with greater soybean cultivation, there is actually lower bee species richness in the Cerrado, thus agricultural expansion is another important factor to increase soybean production in Cerrado. Expanding agriculture provides one common way to improve crop production in this area, but it is also the main factor negatively affecting biodiversity (Aizen et al., 2009; Sommer et al., 2010; Tscharntke et al., 2012b).

2.6 Conclusion

Estimating the spatial distribution of bee species richness and soybean production using remote sensing is important; it helps us to understand the relationship of pollinator and crops at regional scale. Previous studies have analyzed the interaction between pollination services provided by pollinators and crop production under climate change, and they concluded that the decline in pollinator population had a negative influence on crops production (Imbach et al., 2017a; Imperatriz-Fonseca et al., 2017; Marchioro and Krechemer, 2018). In this study, we used remote sensing data to model the spatial distribution of bee species richness and soybean production to understand their response to environment change over time. The proposed model approach provides a novel perspective to analyze the interaction between pollinator and agricultural production at regional scale, and our results indicate that this approach is reliable to use in other similar regions.

Our results clearly illustrated the spatial distribution of the modeled bee species richness and soybean production for the 2000 to 2015 period, however, there are still some parts that need to be improved in future research. First, it is difficult to collect absence data from moving species. Though some methods such as creating pseudo-absences data can help to solve this problem, there still needs to be more advanced methods to improve its accuracy (Barbet-Massin et al., 2012; Leroy et al., 2018b; Schmitt et al., 2017). Second, the crop simulation model is useful for simulating crop information and estimating its influence on environments, but due to the lack of crop cultivar information, we need to collect more data to improve our modeled result in the future. Third, limited by the spatial resolution of remote sensing data, the coarse spatial resolution may have affected the understanding of the interaction between bee species richness and soybean production. Despite these limitations, we believe this study is a fundamental step toward understanding agriculture expansion and pollinators' species richness at the regional scale.

Acknowledgements

The authors thank the Goddard Earth Sciences Data and Information Services Center (GES DICS) for providing gridded environmental dataset without cost, and the Tropical Rainfall Measuring Mission program for providing a precipitation dataset. We would like to thank Allard de Wit for the help with the WOFOST model issues. We also thank the anonymous reviewers who provided helpful comments on the manuscript. DPS received a productivity grant from Conselho Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq – proc. number: 304494/2019-4).

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Chapter 3 - Estimating environmental vulnerability using remote sensing, machine learning and Twitter data

Abstract

Human activities and climate change are among the main drivers of environmental vulnerability, which can cause soil erosion, land degradation and vegetation decline. Quantitively estimating vulnerability can help us understand human impacts on environmental systems. With the development of machine learning algorithms and accessibility of social media data, it is increasingly possible to apply advanced techniques to improve methods for assessing environmental vulnerability. To achieve this goal, we selected five exposure indicators and six sensitivity indicators, then used them to build an environmental vulnerability model. We applied an Autoencoder to find the optimal features in exposure and sensitivity, respectively. We then used the displaced ideal method to estimate environmental vulnerability in the Brazilian Cerrado for the years 2011 and 2016. Finally, we mined related historical Twitter data from these two years to validate the result. The results showed that the different classes of environmental vulnerability areas from low, medium and high were 6.72%, 34.85%, and 58.44% in 2011 and 3.45%, 33.68% and 62.87% in 2016, respectively. The results also showed that highest environmental vulnerability areas were in the southern Cerrado. Moreover, the Twitter data results showed that more than 85% of tweets occurred in the areas considered as high environmental vulnerable class, more specifically in the states of Goiás, São Paulo and Minas Gerais. Our findings indicate that for the selected years, the areas classified as highly vulnerable increased in the Cerrado, and agricultural expansion is one of main reasons. Furthermore, the results also reveal that the Autoencoder algorithm can be used for environmental assessment. In addition, the study shows that social media data has the potential to effectively analyze the

relationship between human activity and the environment. Although our work provides a novel perspective to estimate environmental vulnerability at the regional scale, which can be easily replicated to other regions around the world, it is necessary to develop a more comprehensive data set that can improve model performances in the future.

Keywords: Environmental vulnerability, Remote sensing, Twitter data, Autoencoder, Cerrado

3.1 Introduction

Vulnerability refers to the propensity of environmental systems to suffer harm from external stressors (Adger, 2006; Brooks, 2003; Cutter, 2012; Preston et al., 2011). As one critical component of the effects of anthropogenic activities on the physical environment, estimating vulnerability can help us understand the inherent structure of environmental systems, and provide valuable information to control further hazards, thus building a sustainable environment. Importantly, environmental vulnerability as an interdisciplinary concept has been used in many different fields, such as ecology, agriculture and disaster management (De Lange et al., 2010; Fuchs et al., 2012; McLaughlin and Dietz, 2008). However, focusing on physical environment vulnerability caused by human activities is still a popular topic. Moreover, climate change as one consequence of environmental changes has become the central theme in environmental vulnerability assessment (Fuchs et al., 2012; Füssel, 2007), and some studies have concluded that climate change is one of the important drivers of environmental vulnerability (Berry et al., 2006; Birkmann et al., 2015; O'Brien et al., 2004). For example, extreme events such as unpredicted heavy rain and severe hot weather have caused many environmental problems such as surface soil erosion, land degradation, and drought in many regions of the world (de Oliveira et al., 2017; Gomes et al., 2019). Thus, it is important to estimate environmental vulnerability to consider agricultural expansion and climate change.

Studying the complexity and abstraction of environmental vulnerability at a regional scale is not an easy task, and research has summarized several main vulnerability approaches (e.g., risk-hazard models, pressure-and-release models, expanded vulnerability models, and social vulnerability/adaptive capacity models) to understand environmental vulnerability (Preston et al., 2011). One important common characteristic of all these models is the need to create indicators to evaluate environmental vulnerability (Berrouet et al., 2018; Cutter, 2003; De Lange et al., 2010). However, the most difficult part of using indicators to estimate vulnerability is to identify the relative contribution of each indicator to the total environment (Zhao et al., 2018a). Some studies have used methods such as the Analytical Hierarchy Process (AHP) to weight these indicators in environmental vulnerability assessment (Li et al., 2006, 2009; Qiao et al., 2013). Nevertheless, there are some limitations about these methods such as defining each indicator's weight using the experience of experts (Zhao et al., 2018a; Zou and Yoshino, 2017). Other methods made use of Principal Component Analysis (PCA) and logistic regression as an alternative to define the weight contribution of indicators (Gupta et al., 2020; Nandy et al., 2015; Wei et al., 2020). Though these methods can capture the main characteristic of indicators, part of the information is removed in the model process because of index selection and index weight determination by the dependency of the prior knowledge and experience of researchers.

One potential alternative to overcome the above limitation is the use of machine learning algorithms. These methods can be characterized by their ability to automatically "learn" from the input data, and as a result, to find the optimal weights for each indicator, or to reduce the indicators' dimension (Chandrashekar and Sahin, 2014; Uysal and Gunal, 2012; Wang et al., 2016). For instance, Javadi et al. (2017) used K-means cluster analysis to classify aquifer vulnerability into four different levels. Other studies also used machine learning algorithms to select features when generating representations of input data (Song et al., 2013; Wang et al., 2016). Autoencoder algorithms have been widely used in the remote sensing community to classify remote sensing images (Lv et al., 2017; Ma et al., 2016). Due to their ability to convert the input data into hidden-layers and extract latent representation, Autoencoders can simplify complex processes and be used for dimensionality reduction, and denoising data (Ian Goodfellow, Yoshua Bengio, 2016). For instance, Wang et al. (2016) investigated the dimensionality reduction ability of Autoencoders and concluded that the performance of Autoencoder is better than other algorithms such as PCA. Petscharnig et al. (2017) also used an Autoencoder to reduce the dimensionality of image feature to analyze images. Although these studies have demonstrated that Autoencoder algorithms are robust machine-learning algorithms in features selection, they have not been applied in optimizing environmental vulnerability indictors.

Also, a number of recent research efforts have shown that nontraditional data sources like social media networks can be used to improve modeling performance in disaster management and climate change studies (Cervone et al., 2016; Resch et al., 2018; Rosser et al., 2017). In fact, social media has emerged as a popular way to create, access and exchange user-generated content that is ubiquitously accessible (Batrinca and Treleaven, 2014). Thus, mining useful information from social media has become a potential resource to improve the management of crises, and a great number of research have extracted useful information from social media to analyze flooding, disasters or to map disaster areas (de Albuquerque et al., 2015; Pacifici et al., 2015). Nevertheless, to our knowledge there is no study applying social media data into environmental vulnerability assessment.

It is important to highlight here that we recognize the challenges in estimating physical environmental vulnerability for large-scale systems but collecting data from remote sensing to estimate environmental vulnerability at a regional scale became an efficient alternative (Liao et al., 2013; Song et al., 2015; Zhao et al., 2018a). Although machine learning techniques and social media data have been broadly used in many fields to analyze the relationship between human activities and the environment, their performance in the field of environmental vulnerability is still unclear. Thus, this study has two main objectives. First, we want to test the use of machine learning in optimizing environmental vulnerability indicators that can be used to estimate the environmental vulnerability for large-scale areas such as the Brazilian Cerrado; and second, to test the use of Twitter data in validating the model results for the Brazilian Cerrado.

3.2 Study Area and Data Processing

3.2.1 Study Area

We address the Brazilian Cerrado, the second largest ecoregion in Brazil, as our study area. The region occupies the central plateau of the country and represents 23% of entire Brazilian territory and it is considered one of the most diverse neotropical savannas (Lahsen et al., 2016; Ratter et al., 1997) (Figure 3.1). The Brazilian Cerrado is composed of 11 states with two well-defined seasons: the rainy season from October to April, and the dry season from April to September. The amount of rain in the region is about 800–2000 mm/year, with an average annual temperature of 18–28 °C (Ratter et al., 1997). Because of its unique geographic position, the typical Cerrado vegetation ranges from closed to open canopy deciduous and semi-deciduous forest with shrub to natural grassland (Beuchle et al., 2015b). During decades of agricultural development, the Cerrado has become the leading producer region in Brazil for major export crops, and this region is responsible for the majority of Brazil's planted area in soybean (61%), maize (61%), and cotton (99%) (Bellón et al., 2017; Beuchle et al., 2015b; Dickie et al., 2016). In spite of these significant agricultural achievements, agricultural expansion also has caused soil erosion, land degradation, biodiversity loss, and severe drought problems very recently (Nowak and Schneider, 2017). Thus, due to the availability of the data for the entire region, in this study, we selected the years of 2011 and 2016 to estimate its annual environmental vulnerability.

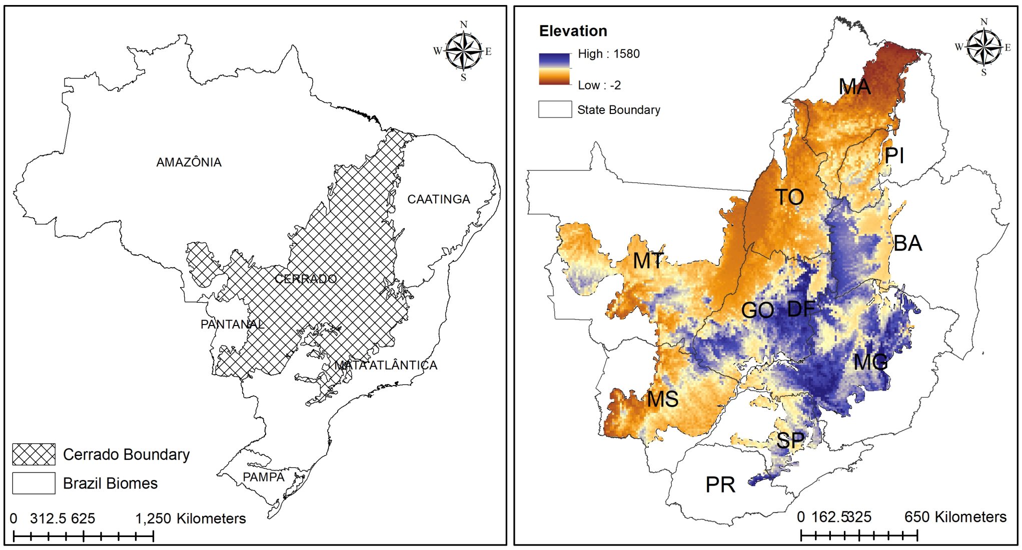

Figure 3.1 The geographic location of the study area and its interacting states. The abbreviations of the Brazilian states' names are as follows: BA: Bahia; DF: Distrito Federal; GO: Goiás; MA: Maranhão; MG: Minas Gerais; MT: Mato Grosso; MS: Mato Grosso do Sul; PI: Piauí; PR: Paraná; SP: São Paulo; TO: Tocantins.

3.2.2 Data preparation

To estimate the environmental vulnerability of the Cerrado, an assessment framework was established with multiple dimensional indicators representing different aspects of the Cerrado environment. These data cover climate data, vegetation health indexes, population data, and Twitter data. Particularly, we collected well-known climate data of factors affecting the environment such as air temperature, precipitation, wind speed, and humidity (Füssel 2007; Skondras et al. 2011; Wirehn et al., 2015). Annual average air temperature, average specific humidity, annual average of 0–10 cm soil moisture, and wind speed were collected from the GLDAS_NOAH025_M 2.1 product with a spatial resolution of 25 km by 25 km. Annual total precipitation was from the TRMM_3B43 monthly product with a spatial resolution of 10 km by 10 km.

As one critical element of the physical environment system, vegetation health is a valuable indicator of the response of the ecosystem to environment changes. To evaluate vegetation health, we collected annual average enhanced vegetation index (EVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) product's monthly Aqua Vegetation Indices product (MYD13C2 V6) with a spatial resolution of 5600 m by 5600 m. Another important factor to consider is the ability of the ecosystem to absorb water and to evaporate to the atmosphere. In fact, the evapotranspiration is one of the most important components of the hydrological cycle and controls the availability and distribution of water on the land surface, which can reflect the water cycle response of the environment (Guangcheng Hu et al., 2015; Matthew F. McCabe and Wood, 2006). We acquired annual total evapotranspiration data from Aqua Net Evapotranspiration's 8-day product (MYD16A2 V6) with a spatial resolution of 500 m by 500m.

Drought is another important factor for environmental vulnerability, especially in savanna areas. There are many drought indexes available in the literature such as Vegetation Condition Index (VCI), Palmer Drought Severity Index (PDSL), and Standardized Precipitation Index (SPI) (Dutta et al., 2015; Quiring and Ganesh, 2010). For this study we selected the Vegetation Health Index (VHI) for its robustness in evaluating vegetation health and crop production (Pei et al., 2018). VHI considers the combination of the vegetation condition and the thermal condition of the vegetation that is derived from the Normalized Difference Vegetation Index (NDVI) and from the daytime land surface temperature (DLST) (Karnieli et al., 2006; Pei et al., 2018). We acquired these two data from Aqua monthly MODIS product MYD11C3 V6 and MYD13C2 V6 with a spatial resolution of 5600 m by 5600 m to calculate the annual average vegetation health index in the Cerrado as follows:

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (1)$$

$$TCI = \frac{DLST_{max} - DLST}{DLST_{max} - DLST_{min}} \quad (2)$$

$$VHI = 0.5 * VCI + 0.5 * TCI \quad (3)$$

Where NDVI and DLST are the monthly average values, and max and min are monthly maximum and minimum values, respectively. The VCI and TCI coefficients are set to 0.5, which assume an even contribution from both indices (Karnieli et al., 2006). VCI values range from 0 to 1 with lower values representing more stressed vegetation conditions and higher values representing optimal conditions. The TCI index also ranges from 0 to 1 with lower values indicating harsh weather conditions, and higher values reflecting mostly favorable conditions.

In addition to the vegetation and climate data, annual population data by municipality was collected from the Brazilian Institute of Geography and Statistics (IBGE), and we used it to calculate the annual population density (Skondras et al., 2011; Zou and Yoshino, 2017). Considering the complexity of the topography in this region, we also acquired relief data, which was calculated from digital elevation model (DEM) data, and soil texture data from the International Soil Reference and Information Centre (ISRIC). It is important to note that all these data have different formats and spatial resolutions. Thus, we first converted those statistical data (the minimum unit is the municipality) into geospatial point data using the spatial analysis tool in ArcGIS 10.7.1. Second, we used the Inverse Distance Weighting (IDW) tool from ArcGIS 10.7.1 to convert them into raster data with 10 km by 10 km spatial resolution. The process of IDW is to interpolate the points, area or pixels into raster dataset as a weighted average of a defined number of neighborhood points by assigning weight spatially (Gupta et al., 2020). Finally, we normalized the spatial resolution of all raster data to 10 km by 10 km.

3.2.3 Twitter data

There are many different social media platforms such as Facebook, Instagram, and Twitter. Twitter, however, has become the main social media platform around the world for collecting public information for academic research because it is cost-effective and has a ubiquitous presence (Batrinca and Treleaven, 2014; Stieglitz et al., 2018). One of the potential utilizations of Twitter data is its geolocation information, which can provide the geographic location of tweets and be integrated into geographic information science (GIS) to analyze the interaction between human activity and the environment. In this study, we used the Twitter platform to mine information that could be reflecting signs of environmental problems in the Brazilian Cerrado. Twitter's historical Application Programming Interface (API) was used to access historical Twitter data from January 1th to December 31th for the years 2011 and 2016 in Brazil. The API allows the user to set multiple words that can be used as filters (e.g., "natural disaster", "natural fire", "drought", "hot weather", "water pollination", "flooding", "soil erosion", "bad environment", and "deforestation") to mine related tweets. Normally, each tweet contains the exact geographical location information (or a bounding box containing four coordinates of longitude and latitude that can approximately locate the place) where the tweet occurred. However, because of the user privacy policy, only ~10% of tweets shared exact geographical location information. Although most tweets do not have exact geographic location, the bounding box can also provide approximate location information. Because all environmental vulnerability indicators have a very coarse spatial resolution of 10 km by 10 km, for those tweets not having exact geo-location information, we calculated the center of the bounding box as the geographical location of the tweets.

After mining the Twitter data, we discarded some tweets based on several rules. First, we removed all the tweets with no identified geographical location. Second, we used ArcGIS 10.7.1 software to extract tweets that occurred only in the Cerrado area. Third, we filtered the tweets that were related to our topic of research and removed those ones that used the same keywords, but they were a metaphor to describe other things. Finally, we converted the target tweets into geospatial point data using ArcGIS 10.7.1 software.

3.3 Methods

3.3.1 The Environmental Vulnerability Model

Generally, vulnerability describes the susceptibility of the system to environmental problems, or the lack of ability to recover from resources depredation (Adger, 2006; Fuchs et al., 2012). Many studies have demonstrated that vulnerability is a function of three factors: (1) exposure to a stressor; (2) effect (also termed sensitivity or potential impact); and (3) recovery capability (Lange et al., 2010; Metzger et al., 2006; B. L. Turner et al., 2003). However, other studies have discussed vulnerability and adaptive ability separately in fields such as hazard management, climate change and social environment management, which means that adaptation is not a necessary part in vulnerability estimation (Brooks et al., 2005; Smit and Wandel, 2006). In this study, we selected six exposure indicators and five sensitivity indicators to create an environmental vulnerability model based on the definition of the Intergovernmental Panel on Climate Change (IPCC) and the potential risks for the local environment related with agricultural expansion (Table 3.1). As we want to estimate its annual environmental vulnerability, for some indicators, we used its average value to represent the entire year's condition.

Since environmental vulnerability indicators came from different sources and to make sure they do not strongly correlate, it is necessary to evaluate their correlation to understand the internal relationship between both indicators. Among different correlation methods, we applied Spearman's rank correlation coefficient. Spearman is a nonparametric method for evaluating the association or correlation between two independent variables (Gauthier, 2001). The advantage of using the Spearman correlation is that it is a measure of a monotonic association that is used when the distribution of data makes Pearson's correlation coefficient undesirable or misleading (Hauke and Kossowski, 2011).

The selected variables can present different contributions to the environmental system. For example, air temperature, precipitation, wind speed, and population density can be assumed to have a positive contribution since higher values of these indicators can easily cause environmental vulnerability. On the other hand, some variables such as enhanced vegetation index and evapotranspiration (ET) have a negative contribution, in other words, their lower values mean higher environmental vulnerability.

Combining all these indicators to estimate environmental vulnerability could affect model performance, to avoid this problem, we standardized the positive and negative variables using following equations (Zhao et al., 2018b):

$$X_p' = \frac{X_p - X_{minp}}{X_{maxp} - X_{minp}} \quad (4)$$

$$X_n' = \frac{X_{maxn} - X_n}{X_{maxn} - X_{minn}} \quad (5)$$

Where: X_p' and X_n' are positive and negative standardized value, and X_p and X_n are the original value of that variable. X_{max} and X_{min} are the maximum and minimum value in that positive or negative variable, respectively.

Table 3.1 The environmental vulnerability model and indicator explanation. Positive contribution means higher value has higher environmental vulnerability, and negative contribution means lower value has higher environmental vulnerability.

Factors	Indicators	Description	Contribution
Exposure	Air temperature (ART)	The annual average of air temperature	Positive
	Humidity (HMD)	The annual average of specific humidity	Negative
	Annual total precipitation (TP)	The total of annual precipitation	Positive
	Wind speed (WIS)	The annual average wind speed	Positive
	Slope (SLP)	Calculated from digital elevation model data (DEM)	Positive
	Soil texture (SOL)	Collected from International Soil Reference and Information Centre	Negative
Sensitivity	Annual average Enhanced vegetation index (EVI)	We collected monthly enhanced vegetation index to calculate annual average enhanced vegetation index	Negative
	Annual average of 0-10 cm soil moisture (SOM)	Annual soil moisture at 0-10cm	Negative

Annual Vegetation health index (VHI)	We collected monthly NDVI and daily LST to calculate annual vegetation health index	Negative
Annual total evapotranspiration (TET)	The total of evapotranspiration by land surface	Negative
Population density (POD)	We collected population per municipality from IBGE and calculate its population density	Positive

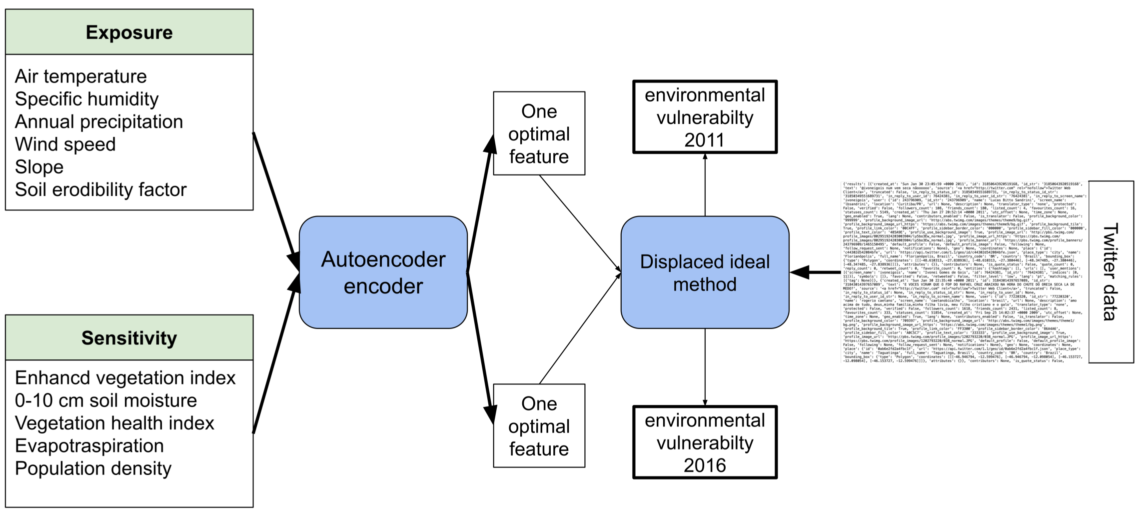

Figure 3.2 The modeling process. We applied autoencoder (round box) to exposure variables and sensitivity variables to generate the optimal feature. Then we used Displaced ideal model (round box) to estimate environmental vulnerability. Finally, Twitter data was used to validate estiamted results.

3.3.2 Environmental vulnerability Estimate

Two steps were used to estimate environmental vulnerability in the Brazilian Cerrado (Figure 3.2). First, we used the Autoencoder algorithm to optimize exposure and sensitivity variables, respectively. Autoencoder is an unsupervised neural network that uses input samples to encode into hidden-layer representation and then decode it to reconstruct the input (Lin et al., 2013; Ma et al., 2016). A good reconstruction ensures that the input signals were properly represented in the lower dimension latent layer during the encoding procedure. We used it to find the most salient exposure feature and sensitivity feature respectively. It is important to notice that there are many different types of autoencoders, such as stacked autoencoders and convolutional autoencoders (Li et al., 2016; X. X. Zhu et al., 2017), which can be used to improve model performance. Considering the volume of input data, we built an Antoencoder algorithm with two hidden layers using the Keras library with Tensorflow backend in Python environment (https://keras.io/), which is a deep learning API written in Python, and provides user friendly interplay functions. Since the Autoencoder is a feedback neural network we decided to apply the Adaptive moment estimation (ADAM) gradient as the optimizer, because the optimizer is a gradient-based optimization algorithm of stochastic objective function and stochastic gradient descent proves to be a very efficient and effective optimization method in deep learning networks (Sharma et al., 2017). The mathematical equations of Autoencoder are as follows:

$$h_i = sigmoid(W_1 x_i + b_1) \tag{6}$$

$$x_i' = sigmoid(W_2 h_i + b_2) \tag{7}$$

$$L(W_1, W_2, b_1, b_2) = argmin_{W_1, W_2, b_1, b_2} \sum_{i=1}^{N} \|x_i - x_i'\|_2^2 \tag{8}$$

Where: W_1 and b_1 are the encoder weight and bias from input (x_i) to hidden layer (h_i), and W_2 and b_2 are the decoder weight and bias from hidden layer to the reconstruct input x'. Sigmoid function is the activation function. L is the minimization of the reconstruction error.

In the second step, we applied the Displaced Ideal (DI) method (Mishra et al., 2017) to estimate the environmental vulnerability. Initially, this method was proposed to calculate the human development index (HDI), which is a statistic composite index of life expectancy, education and per capita income indicators. Recently, some studies have used this method to assess environmental vulnerability, and their results provided evidence that this method can integrate with other methods to improve the accuracy of environmental vulnerability assessment (Wei et al., 2020; Gupta et al., 2020). The DI method is based on the concept that a better system should have less Euclidean distance from the ideal. In the current study, with the optimized exposure and sensitivity features, we calculated the environmental vulnerability using Euclidean distance theory. A lower value means it has lower environmental vulnerability in this study. The processes are as follows:

$$ex'_{ij} = \frac{ex_{ij} - ex_{min}}{ex_{max} - ex_{min}} \tag{9}$$

$$se'_{ij} = \frac{se_{ij} - se_{min}}{se_{max} - se_{min}} \tag{10}$$

$$EV = \sqrt[2]{\frac{(1 - ex'_{ij})^2 + (1 - se'_{ij})^2}{2}} \tag{11}$$

Where: ex_{ij} and se_{ij} are the exposure and sensitivity feature from autoencoder model, and ex'_{ij} and se'_{ij} are the standardized feature. ex_{max}, se_{max}, ex_{min} and se_{min} are the maximum and minimum of exposure and sensitivity feature from Autoencoder model, respectively. EV is the environmental vulnerability, and 1 is the ideal condition.

3.4 Results

3.4.1 Correlation result

In this study, we selected 11 indicators that can potentially be used to model environmental vulnerability in the Brazilian Cerrado. The Spearman's rank correlation coefficient results showed that the indicators do not have very strong positive or negative correlation for the years of 2011 and 2016, thus we used all 11 indicators to estimate environmental vulnerability in the Cerrado (Figure 3.3). For instance, in both 2011 and 2016, soil texture, total evapotranspiration, and vegetation health index had weak correlation with each other. Nevertheless, the results also showed that annual average air temperature has medium negative correlation with population density in 2011 and 2016, and the specific humidity (HMD) has medium negative correlation with wind speed in 2016. On the other hand, the results also found that annual average air temperature had stronger positive correlation with specific humidity in 2011, and total precipitation had stronger positive correlation with surface soil moisture in 2016 (Fig. 3).

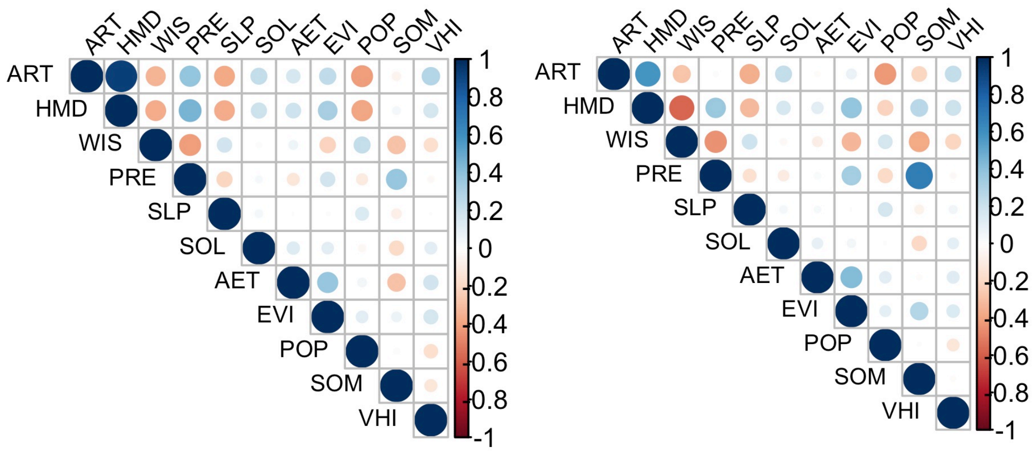

Figure 3.3 The Spearman correlation of variables in 2011 (left) and 2016 (right). ART is the annual average air temperature; HMD is the annual average of specific humidity; WIS is annual average wind speed; PRE is the total annual precipitation; SLP is the slop; SOL is soil texture; AET is the total evapotranspiration; EVI is annual average enhance vegetation index; POP is annual population density; SOM is annual surface (0-10 cm) soil moisture; VHI is annual average vegetation health index

3.4.2 Environmental Vulnerability result and its spatial distribution

We estimated environmental vulnerability of the Cerrado at grid scale with a spatial resolution of 10 km by 10 km. To easily interpret the result, we used ArcGIS 10.7.1 software to classify environmental vulnerability with three classes: low environmental vulnerability (< 0.35), medium environmental vulnerability (>= 0.35 and <= 0.53), and high environmental vulnerability (> 0.53). The division is based on the distribution of value and followed the idea from Wei et al., (2020). In 2011, 6.72% of the Cerrado areas were classified as having low environmental vulnerability, 34.85% and 58.44% of the Cerrado areas were classified as having medium and heavy environmental vulnerability, respectively. However, in 2016, the three classes of environmental vulnerability changed to 3.45% (low), 33.68% (medium), and 62.87% (high) (Figure 3.4). In terms of states, the results showed that the southern Cerrado, especially in the states of Mato Grosso, Góias, São Paulo, and the western part of the Minas Gerais state presented signs of high environmental vulnerability. The results also found that the northern part of the Cerrado presented signs of low environmental vulnerability, specifically in the state of Maranhão and in the northern part of the state of Tocantins (Figure 3.4).

When comparing the years of 2011 and 2016, the results showed significant changes of environmental vulnerability in the states of Mato Grosso, Mato Grosso do Sul, Góias, and Maranhão. For instance, western Góias and eastern Mato Grosso had high environmental vulnerability in 2011, but some places in these two states changed to medium environmental vulnerability in 2016. Oppositely, environmental vulnerability in some areas in Mato Grosso do Sul and western Bahia changed from medium to high. It is also important to note that environmental vulnerability changed from low into medium in some areas in the northern Cerrado (Figure 3.4).

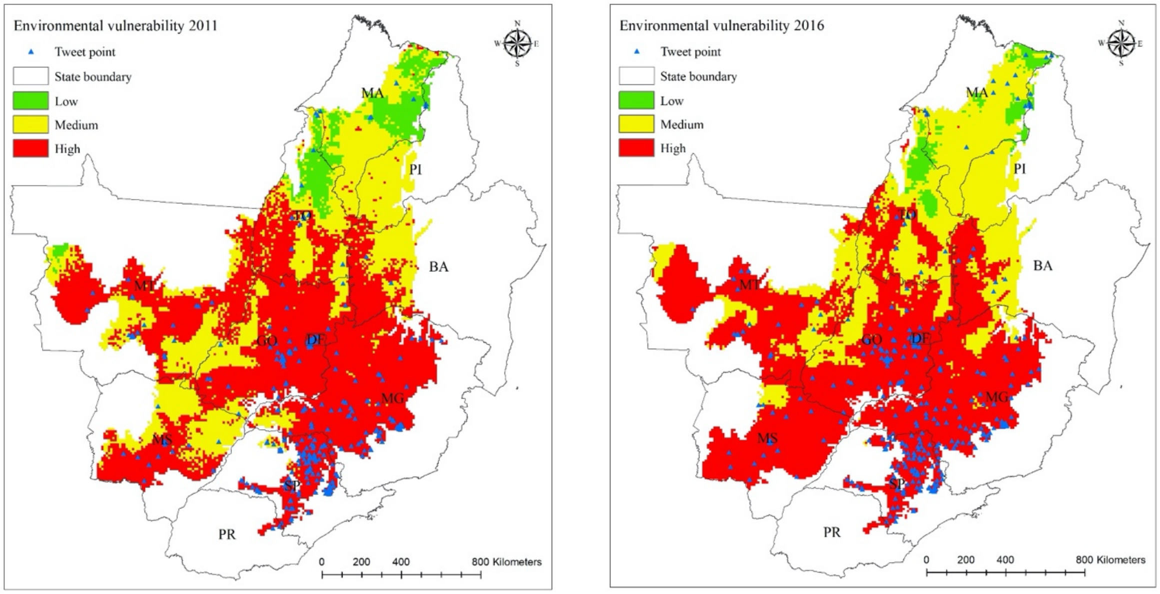

Figure 3.4 Environmental vulnerability maps in the Cerrado for 2011 and 2016 with mined Tweets. The abbreviations of the Brazilian states' names are as follows: BA: Bahia; DF: Distrito Federal; GO: Goiás; MA: Maranhão; MG: Minas Gerais; MT: Mato Grosso; MS: Mato Grosso do Sul; PI: Piauí; PR: Paraná; SP: São Paulo; TO: Tocantins.

3.4.3 Twitter data result

Conducting validation of modeled result is an important task. However, it is difficult to collect validation data, especially when it involves historical information or when it involves a large study area. Twitter is a platform that allows users to describe real time insights or present public opinion on a topic such as the environment. In this study, we mined historical Twitter data that expressed opinions about the environment in the Brazilian Cerrado and used it to validate the environmental vulnerability results. We mined a total of 23,129 and 32,913 tweets for the years of 2011 and 2016, respectively. The mined tweets contained key words that could demonstrate concerns with the environmental in Brazil. We used the geographical location services to select tweets that were located (or occurred) in the Cerrado region. The results showed that there were 2,709 tweets in 2011 and 3,264 tweets in 2016 making references to the key words we chose to represent our topic of interest in the Cerrado region. It is important to notice that although some tweets had key words, they did not describe environmental problems. We removed these unrelated tweets and kept 245 tweets for the year of 2011 and 281 tweets for the year of 2016, which represents 12.29% and 8.61% of all tweets in the Cerrado for 2011 and 2016, respectively (Figure 3.5). The analysis of these tweets brought interesting results. For instance, the number of tweets that occurred in the months of June, July and September were more than other months for 2011. In other words, there were more tweets related to the environment during the dry season in the Cerrado. However, for 2016, the number of tweets in the months of April, June, and August were more than for the rest of the year (Figure 3.5).

To validate the results of the environmental vulnerability, we overlaid the target Twitter data on the environmental vulnerability map. The results showed that 88.57% of the tweets in 2011 and 88.97% of tweets in 2016 were located in the high environmental vulnerability areas (Figure 3.4). However, the results also showed an association between low numbers of tweets with areas classified as low vulnerable areas. Moreover, we listed the number of tweets in each state that are within the Cerrado boundary (Table 3.2), and the results found that some high environmental vulnerability states such as the states of Mato Grosso, Góias, Minas Gerais, São

Paulo, and Mato Grosso do Sul had a higher number of tweets than other states in 2011 and 2016.

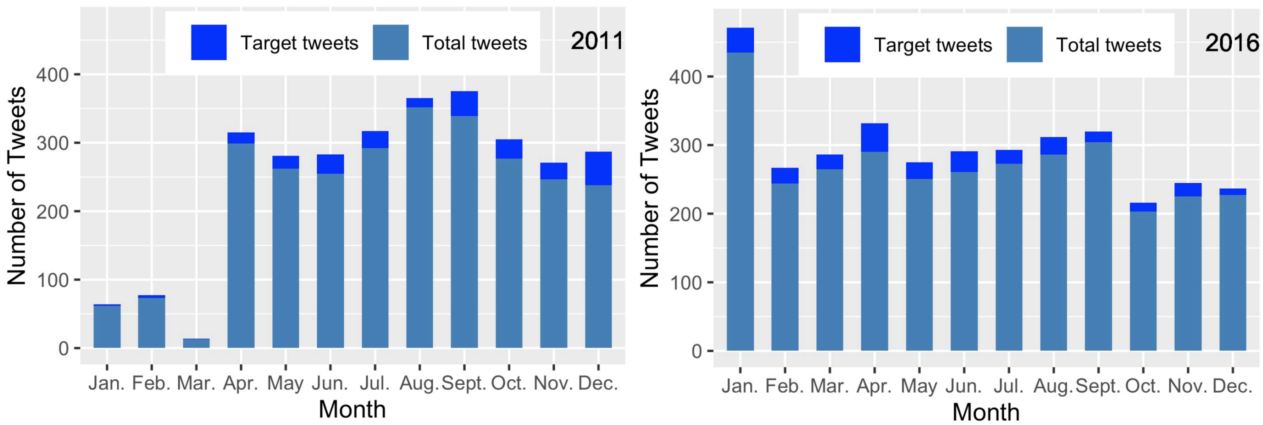

Figure 3.5 Monthly number of Tweets with Key environmental vulnerability Words in the Cerrado at the years of 2011 and 2016.

Table 3.2 Number of tweets in each state within the Cerrado boundary for the years 2011 and 2016

State short name	2011			2016		
	State name	Tweets number	Proportion (%)	State name	Tweets number	Proportion (%)
BA	Bahia	2	0.82	Bahia	6	2.14
DF	Distrito Federal	16	6.53	Distrito Federal	14	4.98
GO	Goiás	35	14.29	Goiás	51	18.15
MA	Maranhão	8	3.27	Maranhão	15	5.34
MG	Minas Gerais	61	24.90	Minas Gerais	80	28.47
MT	Mato Grosso	16	6.53	Mato Grosso	18	6.41
MS	Mato Grosso do Sul	13	5.31	Mato Grosso do Sul	17	6.05
PI	Piauí	3	1.22	Piauí	6	2.14
PR	Paraná	3	1.22	Paraná	1	0.36
SP	São Paulo	87	35.51	São Paulo	83	29.54
TO	Tocantins	11	4.49	Tocantins	10	3.56

3.5 Discussion

3.5.1 Environmental vulnerability model analysis

The purpose of the present study is to estimate the environmental vulnerability of the Cerrado. To estimate the vulnerability of the physical environmental in this region, we highlighted climate effects and collected 11 indicators. Although we kept all selected indicators, there are still some uncertainties. For instance, the possible reason of these stronger negative correlations could be an internal relationship between indicators. In the Cerrado region, there are two well defined seasons: a wet season and a dry season. The two seasons condition caused the imbalance of precipitation, thus affecting the inequality of specific humidity in two seasons. Furthermore, high wind speed could increase the flow of air mass, and consequently it could decrease the humidity in the air.

Other correlations such as the positive correlation between precipitation and soil moisture could be related to the original data limitation. Some scholars have used remote sensing data to analyze the correlation of precipitation and soil moisture, and they concluded that positive correlation exists in these two variables (Sehler et al., 2019). In this study, the total evapotranspiration and enhanced vegetation index also had a positive correlation. Evapotranspiration (ET) (MODIS product) can measure the availability and distribution of water on land surfaces, which is an important component of the surface energy balance. Vegetation canopy is strongly related with ET, and different vegetation types have different ET capacity (Zhang et al., 2016). Similarly, the vegetation index derived from remote sensing can also be used to estimate vegetation condition on the earth surface. The enhanced vegetation index (EVI) in this study provides improved sensitivity in high biomass regions while minimizing soil and atmosphere influences, which can provide more accuracy of vegetation condition compared with traditional NDVI (Son et al., 2014).

Additionally, we used an autoencoder algorithm to generate the optimized features and applied the displaced ideal method to calculate the environmental vulnerability in the Brazilian Cerrado. Our results indicate that the autoencoder is a reliable method to decrease the dimensions of environmental vulnerability indicators. Commonly, this algorithm is broadly used in the remote sensing community to classify imagery or remove image noise (Lin et al., 2013; Ma et al., 2016), but our method provides evidence that it can be used to assess environmental vulnerability.

3.5.2 Environmental vulnerability in the Cerrado

The three classes of environmental vulnerability results indicate that the high environmental vulnerability is the dominating one in the Brazilian Cerrado for the years of 2011 and 2016. The Cerrado region in Brazil has been through enormous agricultural expansion with more than 50% of its area converted into agriculture, which has caused environmental degradation such as soil erosion, land fragmentation with effects in the hydrological cycle (Gomes et al., 2017; Spera et al., 2016a). One potential explanation for the highly vulnerable areas in the southern Cerrado could be related to agricultural development in these states. In other words, the states in this classified region (e.g., Mato Grosso, Góias, São Paulo, and Minas Gerais) have been expanding agriculture since the 1980s, consequently these areas have been through natural environment changes for decades (Cohn et al., 2016; Hunke et al., 2015a). For example, in the state of Góias, sugarcane areas increased from less than 142,000 ha to over 1,080,000 ha, and soy-corn double-cropping areas increased from 373,000 ha to 1,400,000 ha, and in addition, cattle stocking rates also increased 0.07 heads/ha between 2003 and 2016

(IBGE, 2016; Spera, 2017b). These significant agricultural achievements, mostly caused by replacing natural vegetation, could be affecting soil erosion and land degradation. Importantly, with the development of agricultural technology, these above-mentioned crops have helped with the process of agricultural intensification by increasing the agricultural yields of existing land though chemical fertilizers and irrigation (Barretto et al., 2013; Van Asselen and Verburg, 2013). Evidence has also shown that this type of agricultural expansion can positively affect the natural environment by restoring degraded ecosystems and sparing natural vegetation (Barretto et al., 2013; Tscharntke et al., 2012b). Thus, this could explain why some areas in the states of Mato Grosso and Góias had lower environmental vulnerability in 2016 compared with 2011.

Contrasting with the southern part of the Cerrado, the results for the northern Cerrado present areas with lower levels of environmental vulnerability for the years of 2011 and 2016. These areas are known as the new agricultural frontier[1] in Brazil (Araújo et al., 2019; Horvat et al., 2015b) and consequently it has not shown severe environmental problems for the period under investigation. However, with lower land prices than the more established areas and the recognition by the government as a new agricultural frontier, this region will probably become more vulnerable with agriculture expansion and intensification, thus potentially facing the same environmental problems (e.g., soil erosion and water pollution) of others highly vulnerable areas.

Our estimations indicated that lower vulnerable areas changed into medium vulnerable areas in 2011 and 2016. It is also noticeable that the western state of Bahia has more area changed into highly vulnerable area in 2016. This part of the state of Bahia could be considered

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[1] For instance, MATOPIBA is located in this region and it was officially designated in May of 2015 by the Brazilian government as the new agricultural frontier.

as an old agricultural area in the Cerrado (Araújo et al., 2019; Noojipady et al., 2017a), which could be providing evidence that agricultural expansion might be one possible reason for environmental vulnerability in this region. In addition, it is important to note that the Cerrado region has a complex topography that varies from canopy covered forest in the northwest part of the Cerrado to grassland on the high plateau. The forest has a higher vegetation index than grassland, which could give rise to some potential bias in the model, thus causing lower environmental vulnerability (Beuchle et al., 2015a). The complexity of vegetation distribution could also explain the spatial distribution of environmental vulnerability in the Cerrado.

3.5.3 Twitter data and environmental vulnerability

In the current study, we tested the use of Twitter data in validating the model results. The validation indicates that Twitter data is a potentially reliable data set in environmental vulnerability assessment. Thus, our results confirm what other studies have also concluded about the use of this type of data. More specifically that nontraditional data sets such as Twitter data can provide an incredible volume of data to help assess disaster management (Cervone et al., 2016; Wang and Ye, 2018). However, different from these previous studies, our study is the first to use historical Twitter data in the validation of estimates of environmentally vulnerable areas. This is significantly important for considering some problems with uncertainty. For example, many scholars have focused on the development of novel methods to assess environmental vulnerability, but they lacked enough evidence to validate the modeled results (Nandy et al., 2015; Zou and Yoshino, 2017). Considering the size of the study area and accessibility of social media information, data mining of historical Twitter data emerges as a potential solution. Nevertheless, it is important to keep in mind that although the data provides valuable information to help us identify areas of high environmental vulnerability, the internal variation within the historical years need to be carefully evaluated. For instance, one possible reason for a higher number of tweets in 2016 compared to 2011 could be related to the increasing popularity of the Twitter platform in the Cerrado. It is known that the 2011 was the fifth year after Twitter launched and it is not a surprise that the total number in 2011 is less than in 2016. Second, some possible reasons for higher numbers of tweets in some months compared to other months could be related to extreme weather events in these months. For instance, in our study we set filters to mine Twitter data that captured information during the two well defined seasons that occur in the Cerrado region of Brazil (i.e., the dry season from April to September and the wet season from October to March), which could have some unusual climate effects such as very high temperature or insufficient precipitation. Therefore, users could be easily tweeting the context that they were facing by using key words such as hot, dry, or drought, and not necessarily expressing concerns about the vulnerability of the environment. Additionally, it is important to notice that social media data is more commonly used in developed or dense residential areas (Stieglitz et al., 2018). This could also explain why there are more tweets in the state of Góias, Minas Gerais, and São Paulo when compared with very fewer tweets in the northern states of Piauí and Bahia (Table 3.2). Finally, when comparing streaming Twitter data with historical data, a potential drawback emerges. The historical Twitter data volume is much smaller due to increasing popularity over time. For instance, in the current study, although we mined more than 20,000 tweets for the selected years, the total number of useful tweets in the Cerrado had just hundreds of tweets, which could be affecting the results.

3.6 Conclusion

The development of environmental vulnerability indicators is a critical method to analyze the consequence of human activity in the environment. In this study, we used an Autoencoder algorithm to generate optimal features of exposure and sensitivity with a Displaced Ideal (DI) method to calculate the environmental vulnerability of the Brazilian Cerrado for the years of 2011 and 2016. In doing this, we also tested the use of Twitter data in validating the modeled results. The proposed methodology was able to provide a novel approach to estimate the environmental vulnerability for a large-scale area by combining the use of remote sensing data with machine learning. This approach overcomes the approach of assigning weight to model variables with the intent of improving the accuracy of the results. Our results also indicate that machine learning and Twitter social media data have potential for estimating and validating environmental vulnerability models.

It should be emphasized that the proposed methodology still has some limitations that need to be addressed in the future. First, we chose 11 vulnerability indicators to estimate the environmental vulnerability in the Brazilian Cerrado based on local environmental conditions. However, because of the complexity of the study area, it is difficult to develop indicators to represent all possible environmental conditions in this region. Second, to estimate the annual environmental vulnerability of the Brazilian Cerrado, we take the average value to be the entire year's condition, which could give rise to potential errors due to monthly internal variation. Third, because of the limitations of field data collection, we used Twitter data to validate our results but recognizing some potential shortcomings. For example, the geolocation of tweets is not a required information in tweet due to the user's privacy policies. Although we can use bounding box to approximately locate the tweets in the study area, the actual location of in-situ reports is still uncertain. Instead of these limitations, the findings can shed light on the environmental assessment field and the proposed method can be replicated to other similar regions around the world.

Acknowledgments

The authors would like to thank the Goddard Earth Sciences Data and Information Services Center (GES DICS) for providing the gridded environmental data free of charge, and to the Tropical Rainfall Measuring Mission program for providing the precipitation data. We also appreciate the Land Processes Distributed Active Archive Center (LP DAAC) for providing MODIS land products. We are thankful Dr. Katherine S. Nelson for insightful comments and discussion to improve the quality of the manuscript. We also appreciate the help from the KDD lab in the Computer Science department. We also thank the anonymous reviewers who provided helpful comments on the manuscript.

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Chapter 4 - Map agricultural expansion areas in the Matopiba region using Conv-LSTM model

Abstract

Accurately mapping agricultural areas is important to help us understand the interaction between human activity such as fire activity and the environment. Deep learning algorithms are broadly used in the remote sensing community, but it is still unclear for mapping agricultural areas considering spatial, spectral, and temporal scales. This study seeks to map two agricultural areas and estimate their interactions with burned areas. We proposed a hybrid deep learning algorithm combining convolutional neural network (CNN) and long short-term memory (LSTM) to classify vegetation-covered areas in two interested areas in the Matopiba region in Brazil in September 2012. We prepared features as band 1, band 2, band 3, band 4, and SAVI. All bands information is derived from MCD43A4 MODIS product and has a spatial resolution of 478 m by 478 m. In the model, the CNN part can learn spatial correlation for each pixel from input data, and the LSTM part can learn the temporal scale of the input image. The overall accuracies of classification in place A and place B are 79% and 77% respectively compared with the MCD12Q1 annual land use and land cover product. After analyzing the burned areas that came from the MCD64A V6 product for the same month, the results found that most burned areas happened in the grasslands in the place A, and forestland in place B. Meanwhile, the results also found that burned areas easily occurred at the edge of cropland. Our findings indicate that the proposed model is reliable for classifying time series remote sensing images, and the performance depends on the spatial distribution of each land use type in the study area.

Furthermore, the findings also reveal that fire activities are still one of the most common ways to expand agriculture in the Matopiba region.

Keywords: CNN, LSTM, land use and land cover, classification, remote sensing, burned area

4.1 Introduction

Land use and land cover change is still an effective method to understand the interaction between human activity and environmental changes (Deng and Li, 2016a; Meyfroidt et al., 2013; Van Asselen and Verburg, 2013). Mapping different types of land use and overlaying with burned area can estimate the influence of fire activity on the environment. Fire is an important environmental management tool to maintain ecosystem health (Andela et al., 2017; Hall et al., 2016). On the one hand, it can reduce the amount of biomass present on the landscape or control wild flora and fauna, which can improve the adaptability of the species (Beringer et al., 2007; Randerson et al., 2012), on the other hand, it shapes vegetation structure and composition (Dubinin et al., 2010; Lizundia-Loiola et al., 2020). Although natural fires can maintain the health of ecosystems and update vegetation construct, fire activity is both a common way to expand agriculture but also one of the major contributors to air pollution (Beringer et al., 2007; Chuvieco et al., 2016; Ravindra et al., 2019; Yin et al., 2017). For example, Sun et al. (2016) mentioned that hundreds of millions of agricultural crop residue burned each year in China has already became one of the important global sources of CO_2 emissions. Some studies also stated that fire activities are one important way to develop agriculture in some regions around the world (de Araújo et al., 2012; Pivello, 2011).

To understand the interaction of fire activity and land use types, currently the primary dataset is still remote sensing images, because of its cost-effectiveness and continuous record

(Deng and Li, 2016b; Huang et al., 2002). The multiple spectral resolution of remote sensing data can provide useful reflectance information with different wavelength intervals to help us identify different types of land use and land cover types. Classifying remote sensing images is the most common and challenging method to understand land use and land cover types, and many different methods exist (Mountrakis et al., 2011; Whiteside et al., 2011; Xu et al., 2005; Zhang et al., 2019). Among them, machine learning algorithms have been broadly used in the remote sensing community due to their higher performance (Kavzoglu and Colkesen, 2009; Pal and Mather, 2003; Rogan et al., 2008; Shao and Lunetta, 2012). For instance, Huang et al. (2002) assessed the ability of support vector machines for land cover classification and they concluded that support vector machines outperform other machine learning algorithms. Ramo et al. (2018) tried four traditional machine learning algorithms to map the global burned areas, and discussed their difference based on their results and validation data. Using Landsat images, Luo et al. (2019) also tried support vector machine and decision tree to classify dam disaster areas. Though these machine learning algorithms can achieve better performance than statistical methods, their main drawback is that they cannot consider the spatial correlation with surrounding pixels in remote sensing images.

Compared with these traditional machine learning algorithms, deep learning models, such as convolutional neural network (CNN) and recurrent neural network (RNN), because of their ability to consider spectral, spatial and temporal information of remote sensing images, has caught the attention of many scholars (Castelluccio et al., 2015; Liu et al., 2016; Maggiori et al., 2016; Zhu et al., 2017). As the most popular deep learning algorithm, CNN has been broadly used in the remote sensing community to classify images. For example, some studies use CNN to classify hyperspectral and large-scale remote sensing images and they concluded that CNN performed than other machine learning algorithms for image classification (Paoletti et al., 2018; Yu et al., 2017). Later on, some studies improved on the CNN based on the characteristics of remote sensing images, such as fully convolutional network and 3D convolutional network, and these implications can decently improve the accuracy of classification (Li et al., 2017; Maggiori et al., 2016; C. Zhang et al., 2018). The advantage of the Convolutional Neural Network is that it can consider the spatial construction of pixels, which can improve classification accuracy (Zhang et al., 2016). However, the limitation of CNN is that it is difficult to consider the temporal resolution of remote sensing images, especially when mapping time series images. Recurrent Neural Networks (RNN), however, can elegantly avoid this kind of problem thought learning sequence data. The general idea of the Recurrent Neural Network is the neural network can generate a memory with time change and use it to learn next time step, which has been broadly used in speech recognition, signal processing, and natural language processing (Ienco et al., 2017; Mou et al., 2017; X. Zhang et al., 2018).

Nevertheless, the common problem about the RNN is gradient vanishing and exploding (Ndikumana et al., 2018). To overcome it, scholars have updated RNN and the most popular ones are Long Short-Term Memory (LSTM) and Gate Recurrent Unit (GRU) (Cheng et al., 2016; Dey and Salemt, 2017; R. Fu et al., 2017). For example, some studies using LSTM to classify cropland used time series remote sensing data (Shi and Pun, 2018; Sun et al., 2019). Importantly, many applications need to consider the spatial variation and temporal scale of remote sensing images at the same time. For example, Donahue et al., 2017 published long-term recurrent convolutional networks for visual recognition and description, and Shi et al., 2015 created a convolutional LSTM network to predict climate for near future time and they concluded that the proposed model captured spatial and temporal correlation better. However, very few studies combined these two deep learning algorithms to classify remote sensing images with coarse spatial resolution.

In recent years, with climate change and agricultural expansion around the world, wildfires have become a serious problem. Estimating its interaction with land use and land cover is an important task under current environment scenario. The goal of this study is to create a deep learning model to classify MODIS images and analyze its interaction with burned areas in the Matopiba region, which is a new agriculture frontier in Brazil. We have a three-fold aim: (1) to build a convolutional neural network and long-term short memory deep learning (Conv-LSTM) model; (2) to classify two agricultural areas chosen from the Matopiba region; (3) to estimate the interaction between burned areas and classification results.

4.2 Material and method

4.2.1 Study area

We addressed our study area in the Matopiba region (Brazil), which interact with parts of the states of Maranhao, Tocantins, Piaui and Bahia (Salvador and de Brito, 2018). The region has a two-season climate. The dry season is from April to September and the wet season is from October to March. During these last three decades, this region has experienced enormous agriculture expansion, with more than 50% of the natural vegetation being converted into agriculture areas (Horvat et al., 2015; Salvador and de Brito, 2018). For example, in 2014–2015, the Matopiba region contributed 9.4% of the 209.5 million tons of grains produced in Brazil (Araújo et al., 2019). However, besides continuous agriculture expansion, environmental problem caused by fire during the dry season also caught the attention of scholar. Mapping vegetation covered areas and estimating their spatial distribution with burned areas can help us understand the interaction between human activity and environment. In this study, we selected two places in the Matopiba region to generate land use maps in September at 2012 based on the availability of the data. The two places have the same extent with 420 *420 pixels (~40572 km2) and the spatial resolution is 478 m by 478 m. The place A crosses four states, but most of the study area is in the western state of Bahia and eastern state of Tocantins; and place B interacts with the states of Maranhao and Piaui (Figure 5.1). Land use and land cover in both places is dominated by cropland, grassland and forestland (savanna).

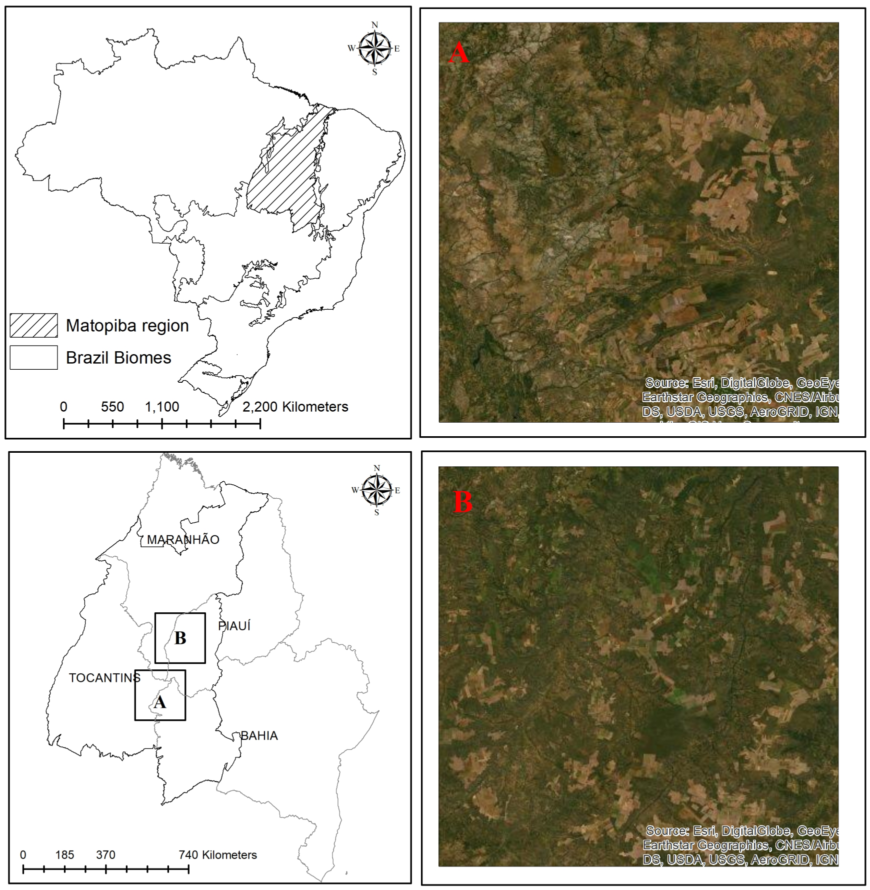

Figure 4.1 The geographic location of the Matopiba region and two selected places A and B with world imagery derived from ArcGIS services.

4.2.2 Data source

Considering the size of the study area, we chose MODIS product with a spatial resolution of 478 m by 478 m. Reflectance plays an important role in identifying the object on the land surface, because visible wavelengths such as blue, green and red can be easily interpreted and they are broadly used in remote sensing classification (Ke et al., 2015; Roy et al., 2016). In this study, we selected the MCD43A4 V6 product as our main data set, because this product uses the Nadir bidirectional reflectance distribution function (BRDF) – adjusted reflectance, which already removed the view angle effects caused by sensor (Schaaf and Wang, 2015). Based on its moderate spatial resolution and land use structure in study areas, we focused on classifying cropland, grassland and forestland in these two places. Though there are some roads, water bodies or developed areas in the study area, because they took less than 2% of the whole study area, we assigned them as grassland in this study.

We used the last day of September (Julian day is 274/275) as our research data because we also wanted to estimate the relationship between land use and burned areas at these two places in the dry season, and the last day of September can record fire activities for the whole month during the dry season. The fire season in the Cerrado is from May to September and September has more fire activities than other months (Pivello, 2011; Rodrigues et al., 2019). The most common problem of classifying remote sensing images is the cloud problem, which could affect the classification result, and the other reason that we chose September is that both places have less than 2% of cloud cover, which can remove potential errors during the data process.

The MCD43A4 V6 product has seven shortwave bands, with band 1 (620–670 mm), band 2 (841–876 mm), band 3 (459–479 mm), band 4 (545–565 mm), band 5 (1230–1250 mm), band 6 (1628–1652 mm), and band 7 (2105–2155 mm). We selected band 1, band 2, band 3, and band 4 for our features. Meanwhile, we also calculated the Soil Adjusted Vegetation Index (SAVI), which is the vegetation index considering the influence of soil, and some studies also pointed out that soil background condition is also one of important factors affecting the vegetation index, especially in the dry season (Ren et al., 2018). The data set and features we used in this study are listed in Table 5.1.

Table 4.1 The date of remote sensing images and classification features used in this study

Remote sensing data	Band 1 (620~670mm)	Band 2 (841~876mm)	Band 3 (459~479mm)	Band 4 (545~565mm)	SAVI
Julan273, 2007	1	1	1	1	1
Julan275, 2008	1	1	1	1	1
Julan273, 2009	1	1	1	1	1
Julan273, 2010	1	1	1	1	1
Julan273, 2011	1	1	1	1	1
Julan274, 2012	1	1	1	1	1

Classifying historical remote sensing images has the problem that it is difficult to find inventory data to validate results. To overcome this problem, we collected the MCD12Q1 V6 annual land use and land cover product with the same spatial resolution with our input data, which is a global land use and land cover product (http://LPDAAC.usgs.gov). Besides this data set, we also collected the Mapbiomas annual land use and land cover product with a spatial resolution of 30 m by 30 m, which is the professional land use and land cover product in Brazil and it broadly used in many remote sensing classification studies (Luo et al., 2019).

To estimate its interaction with burned areas, we also collected monthly burned area data. The MCD64A1 V6 monthly MODIS product was used in this study because it has the same spatial resolution as the MCD43A4 product, and the accuracy of this product is outstanding compared with other products (Belenguer-Plomer et al., 2019; Giglio et al., 2018).

4.2.3 Deep learning model structure design and process

To classify land use in places A and B, the Conv-LSTM model is proposed, which combining the convolutional neural network (CNN) and long short-term memory (LSTM) algorithms. The CNN algorithm can help us to extract features considering its spatial correlation with neighbor pixels from the image, which can optimize features and reduce computing time. The LSTM part is used to determine the temporal scale influence of the remote sensing image. Because remote sensing images are not normal RGB images and lack a sufficient data set to apply deep learning (Paoletti et al., 2018), we used a batch-based method to create overlapping patches that fit the input data format to the CNN model (Maggiori et al., 2016; Sharma et al., 2017). Considering the spatial construction of different land use types, 15*15*5 of each patch was created representing width, height and depth. One disadvantage of this method is that patches from the edge of remote sensing images could cause potential bias, because it either fills 0 to generate designed patch size or removes edge pixels (Chen et al., 2016; C. Zhang et al., 2018).

The general idea of the CNN is to build a filter to cross the whole image to collect useful information, then a pooling layer will be generated by extracting abstract information. Usually we need to create a couple of convolutional layers to fully understand the original image. Then we add a fully connect layer to flatten output of the polling layer and apply a normal neural network to get the final result. In our CNN part, we created three convolutional layers, but just added a max pooling layer for the third convolutional layer (Figure 4.2). Since patch size is 15 by 15 pixels, we set the filter to 5*5 in both places during the CNN part. To avoid data missing, we used the padding method to get the same extent with the input data in the first convolutional layer. After three convolutional layers, we flatten the output and went into LSTM part.

Recurrent neural networks (RNNs) are well-designed machine learning techniques that stand out for their ability to manage sequential data sets such as time serial images. Contrary to convolutional neural networks, they can determine the spatial correlation of pixels, RNNs can consider the changes of the same pixels over time. To avoid common vanishing or exploding problems in the RNN, in this study, we selected Long Short-Term Memory (LSTM), which has a long memory part and short memory part and three different gates. These gates have two major functions: (1) They regulate the quantity of information to forget/remember during the process; and (2) they deal with the problem of gradient disappearance/bursting. Among different types of RNN such as one to one, many to many and many to one, in this study, we stacked two LSTMs, the first one being many to many type, and the second one being many to one type. Finally, we add normal neural work to generate a result, and a SoftMax layer is stacked on the last recurrent unit to predict the final multi-class. The SoftMax priority is given instead of the Sigmoid function, because the value of the SoftMax layer can be considered as a probability distribution on classes that total up to 1 (Peng et al., 2017). The process of the proposed model is list at Figure 4.2.

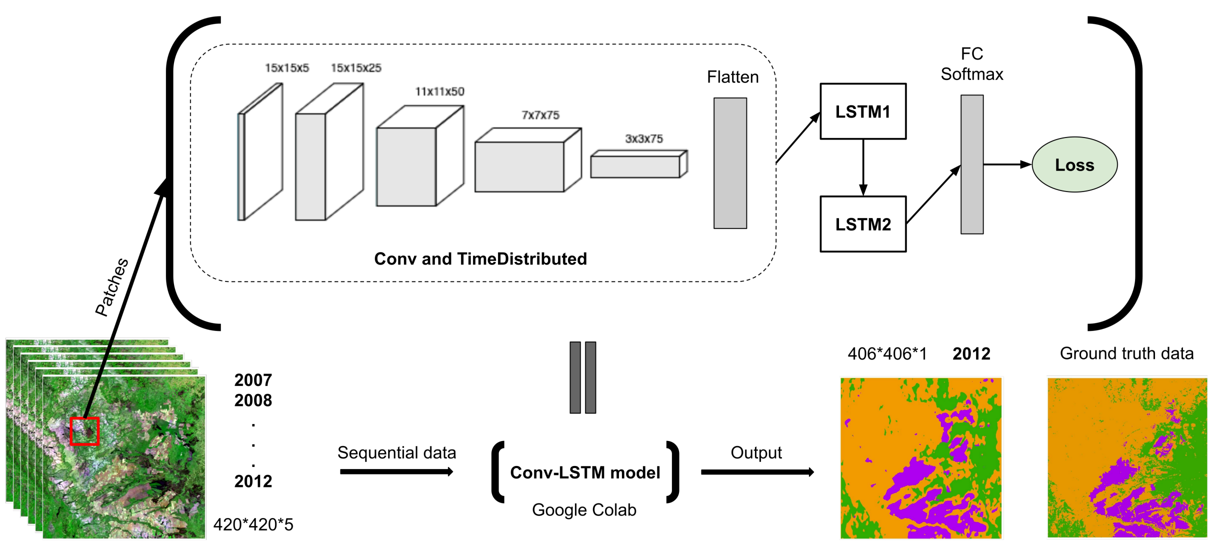

Figure 4.2 The process of the proposed model. The bracket is the classifier model part, wherein we used the multiple patches created from time serial remote sensing images (red

box). The right side of the image is the classification result and ground true data (MODIS product).

To classify remote sensing images in places A and B, we prepared multiple layers image data (with 420 * 420 pixel and 5 depths) and we sequenced these six years of data for 2007, 2008, 2009, 2010, 2011, and 2012. To train this proposed model, we manually collected each land use type's training label around the study areas using existing land use maps and Google Map. Then, we tired the feature images with labeled the image as input for the model. We implemented the model though the Keras python library with Tensorflow as the back end (https://keras.io/) because this library is built on the top of the Tensorflow and it is easy to use. To combine the CNN and LSTM algorithms, we used the Timedistirbuted function in the Keras to wrap all convolutional layers.

During the modeling process, we experimentally found that the best performance of the first LSTM output dimension is 35 and the second LSTM output dimension is 10. To train the model, we used a rectified linear unit (ReLU) activation function during the model process, which is a powerful activation function in the deep learning model with less computer calculation time and higher accuracy, and we selected categorical cross entropy as the loss function because of its the standard loss function used in all multiclass classifications (Paoletti et al., 2018; Sharma et al., 2018; C. Zhang et al., 2018). Then we used Adam optimizer with a learning rate of 0.00001. The Adam optimizer is a first-order gradient-based optimization algorithm of feedback to the neural network, which is the most common optimizer in the deep learning model because of stochastic gradient descent that proves to be a very efficient and effective optimization method in recent deep learning networks (Kingma and Ba, 2015). The experiment is trained for 40 epochs, with a batch size set at 1 using the Google Colaboratory platform with XLA_GPU.

4.2.4 Model validation and data analysis

For the model validation purpose, we used the CNN part of the proposed model (CNN model) to classify the same remote sensing image in September 2012 by replacing Adam optimizer with Stochastic gradient descent (SGD) optimizer (Hutchison and Mitchell, 1973) and set its learning rate as 0.0001. In classifying remote sensing images, it is important to validate the model performance and evaluate classification results. The most important step about classification is to validate the results. When classifying remote sensing images, there are two parts that need to be validated. To achieve good results, we need to validate the classifier model, for which we have a loss function to help us monitor the model. The second part is the classification result. In this study, we used inventory the MODIS MCD12Q1 V6 product as the reference data to validate our classification results. Particularly, we created a confusion matrix to evaluate the performance for each land use.

To estimate the interaction between burned areas and land cover maps, we used our classification results for the last day of September to overlay the monthly burned areas map, which is a widely used burned area product with the MODIS MCD64A1 V6 product. Particularly, we overlaid classified results and burned areas to analyze their spatial distribution and calculated the proportion of burned areas in each land use type.

4.3 Results

Using the proposed model, we classified remote sensing images (September 2012) from places A and B, and we used the MCD12Q1 V6 land use and land cover product to validate our results. Overall, the accuracy of place A is 79%, and place B is 77%, and different land cover types had different performances (Table 4.2). In place A, all three land use types had decent accuracy and the accuracy of grassland extended 85%, but in place B, grassland had the lowest accuracy (less than 50%). Moreover, the cropland and forestland in place B had a better performance than place A, with more than 70% and 95% respectively. Meanwhile, we also visually compared the results with Mapbiomas annual land use and land cover product, which is broadly used in the academic field with its spatial resolution of 30 m by 30 m (Figure 4.3). The results showed that our results are much closer to the Mapbiomas product. For example, compared with our results, the MODIS product, and the Mapbiomas product, the cropland in our results are visually closer with the Mapbiomas product. Similarly, grassland in place B of our result is closer to the Mapbiomas product (Figure 4.3).

Table 4.2 The confusion matrix made with classification results and reference data with the CNN model and Conv_LSTM model

		cropland	grassland	forestland	**Precision**	**Recall**	**F1-score**	**Accuracy**
Place A CNN	cropland	13336	7101	429	0.52	0.64	0.57	0.68
	grassland	11433	76499	18115	0.78	0.72	0.75	
	forestland	846	14788	22289	0.55	0.59	0.57	

		cropland	grassland	forestland	**Precision**	**Recall**	**F1-score**	**Accuracy**
Place B CNN	cropland	5032	5682	1638	0.40	0.41	0.40	0.59
	grassland	3835	12841	8118	0.20	0.52	0.29	
	forestland	3647	45125	78918	0.89	0.62	0.73	

		cropland	grassland	forestland	**Precision**	**Recall**	**F1-score**	**Accuracy**
Place A Conv-LSTM	cropland	17109	3700	57	0.65	0.82	0.73	0.79
	grassland	8326	87180	10541	0.86	0.82	0.84	
	forestland	804	10622	26497	0.71	0.7	0.71	

		cropland	grassland	forestland	**Precision**	**Recall**	**F1-score**	**Accuracy**
Place B Conv-LSTM	cropland	7951	4247	154	0.70	0.64	0.67	
	grassland	2945	16590	5259	0.37	0.67	0.48	0.77
	forestland	530	23984	103176	0.95	0.81	0.87	

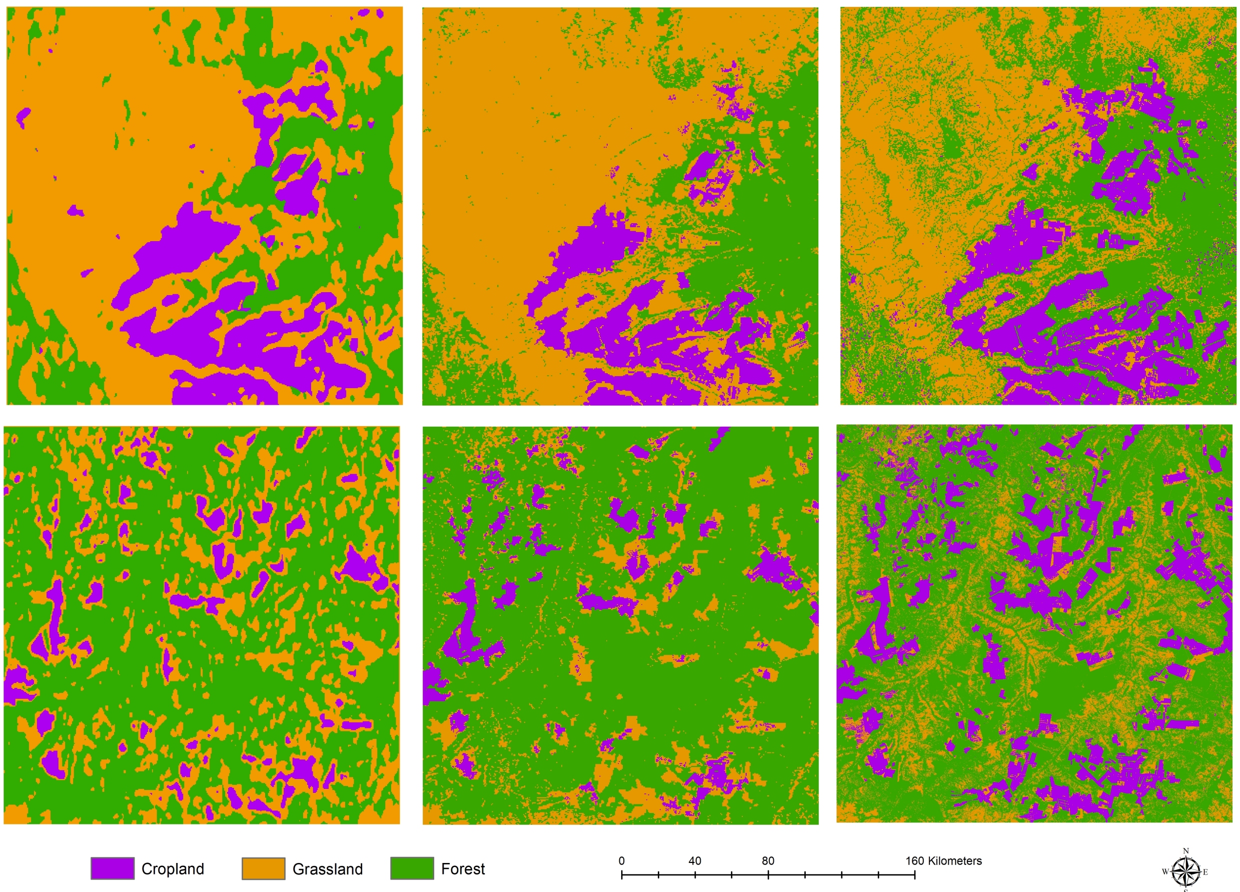

Figure 4.3 The classification result (left), MOD12Q1 LULC product (middle), and Mapbiomes map product (right). Top three maps are place A and bottom three maps are place B.

The classification results also show that in place A, grassland is the dominant land use type and it covers more than half of the study area. The large pattern of cropland is in the southern study area, but the forestland is randomly distributed in the northeast and the southwest corner in place A (Figure 4.3). In place B, the dominant land cover was forestland, and grassland

and cropland are randomly distributed in the study area where they are connected with each other (Figure 4.3).

The other goal of this study was to estimate the interaction between burned areas and classification results. In this region, September has more fire activities than other dry season months, which is also the month farmers need to prepare for the up-coming crop growing season. The overlaid analysis results showed that there are 14.13% burned areas in place A and 13.25% burned areas in place B. The cropland had lowest burned areas in both places, and they were 0.08% and 0.09%, respectively. Meanwhile, the results also found that grasslands were 9.55% in place A, and 12.27% burned areas occurred in the forestland in place B (Table 4.3). Spatially, our results showed that more burned areas happened in grasslands in place A, and more burned areas happened in forestlands in place B. In addition, our results also found that most of burned areas happened at the edge of the cropland in both places (Figure 4.4).

Table 4.3 The proportion of burned areas in each land cover types in place A and B

Land use types	Place A	Place B
Unburned	85.87	86.75
Burned_cropland	0.08	0.09
Burned_grassland	9.55	0.90
Burned_forestland	4.50	12.27

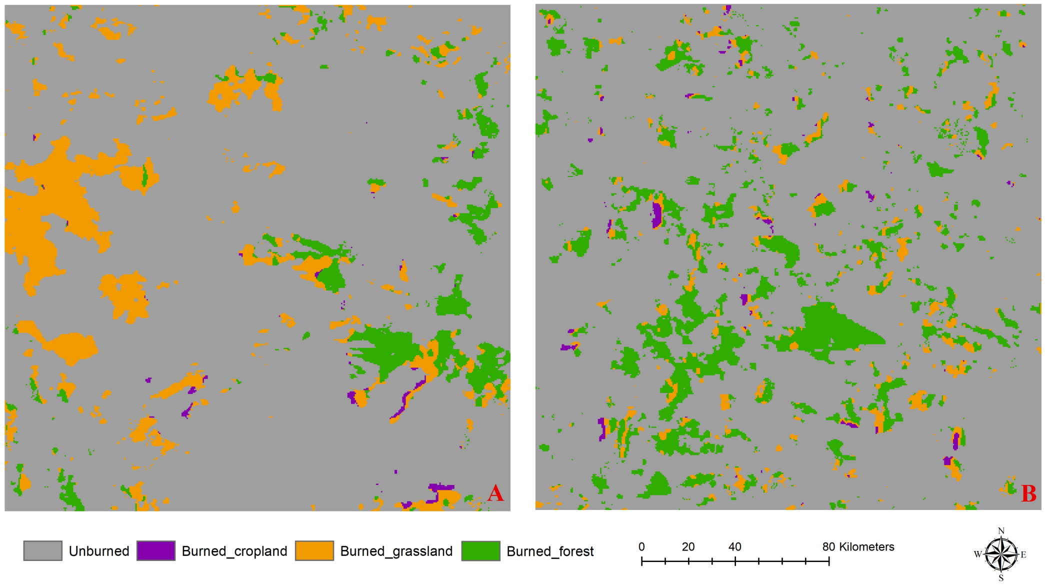

Figure 4.4 The spatial distribution of burned areas in each land use type. Left image is place A and right image is place B

4.4 Discussion

4.4.1 Model evaluation and analysis

In this study, we collected time serial MODIS remote sensing images and created a CNN-LSTM model to classify land use and estimate its interaction with burned areas at two places in the Matopiba region. The proposed model can mainly classify each land use type, and the decent overall accuracy in place A and B have several explanations. First, the input data are chosen from the last day of September, which is in the dry season, and most cropland are in the fallow condition, which could be difficult to classify as grassland because of the confused reflectance values. Some studies also reported this problem when they classified remote sensing images in the savanna area (Luo et al., 2019). Second, the MODIS product has a coarse spatial resolution, which cannot record details about the land use information in one pixel, especially with mixed land cover types. Although these two places have large-scale cropland, the edge of cropland could mix with grassland or forest, which increase the error. Third, one major problem with classifying historical land cover types is the difficulty finding reference data. In the current study, we used the MCD12Q1 V6 product (IGBP) as reference data to calculate classification accuracy, the lower values in both places could be caused by the quality of the MCD12Q1 product. Meanwhile, we also visually compared our results with Mapbiomas annual land use and land cover product, and the classification results provide more evidence that the proposed model is a reliable one to classify time serial remote sensing images with coarse spatial resolution (Figure 4.3).

The proposed model in the current study is novel; it combines convolutional neural network (CNN) and long short-term memory (LSTM) algorithms to learn the spatial and temporal resolution of MOIDS remote sensing image at the same time. Although the CNN can also be used to classify time serial remote sensing images (Li et al., 2017; Pelletier et al., 2019), the RNN is still the primary one because it outperforms on sequential data (Gamboa, 2017; X. Zhang et al., 2018). Integrating these two popular deep learning algorithms, our empirical results showed the proposed model can work on different places with different land cover spatial distributions. For example, place B has more fragmented land use, such as cropland and grassland, which increased the difficulty of classification. However, the overall accuracy of place B can also reach to 77% compared with the existing data set. Furthermore, one difficult step to classify remote sensing images using a deep learning model is the lack of enough training data, and one effective solution is to build patches (Sharma et al., 2017; C. Zhang et al., 2018). It can create small patches from the original image and increase the volume of input data to improve the performance of the model. Our result indicates that this method is a robust method for classifying remote sensing images using a deep learning model. Compared with one dimensional (pixel-based) input data, this way we can take into consideration neighbor pixel information, which is important for remote sensing images because some objects on the land surface generated by patterns such as grassland, cropland, and forestland. In addition, there are many studies on using CNN or LSTM algorithm to classify multispectral or hyperspectral remote sensing images; the input data has fine spatial resolution, and their results showed that these deep learning models outperformed traditional machine learning algorithms (Paoletti et al., 2018; Shi and Pun, 2018; Yu et al., 2017). However, our results added more evidence that the proposed model can also classify remote sensing images with coarse spatial resolution and the model can improve the accuracy of time serial remote sensing images.

Additionally, the proposed model also presents some limitations. For instance, the border effects problem is a common problem in image processing using the CNN model. In this study, we created overlapping patches in each remote sensing image, but we did not consider the edge of the images, which could lose some edge information depending on the chosen patch size. Besides, although the Tensorflow library provides a method to fill this gap, with a limited data set such as remote sensing images, the artificial patches could affect the model performance because of the filled values. Some studies used alternatives such as a full CNN to solve the problem (G. Fu et al., 2017; Maggiori et al., 2016), but we did not apply it in this study. We admitted that more work needs to be done in the future to solve the problem.

Finally, the reason we created the proposed model is to classify the time series remote sensing image at the agricultural expansion areas, which the changing land use and land cover could affect the classification results. To test the ability of the proposed model, we also used the CNN model to classify the same remote sensing image and the results from the table 4.2 indicated that the proposed model indeed improves the classification. The results revealed that the proposed model is reliable for time series remote sensing classification.

4.4.2 Classification result analysis

Place A and B have slightly different overall accuracies and the different overall accuracies are associated with the spatial distribution of each land use in places A and B. The place A we chose has three land cover types, and each of them can easily generate patterns, however, the same three types of land use in place B are more fragmented and grassland and forestland are mixed with each other. This complex spatial distribution in place B caused the difficulty of selecting training data, which plays a critical role in the proposed model. Importantly, instead of classifying a single remote sensing image, we collected time series remote sensing images and considered the temporal variation of the same pixel over time to apply to the proposed model. Taking advantage of the CNN algorithm, we can determine the image's spatial correlation, and from the LSTM algorithm, we can learn each pixel's temporal variation; the classified results should be better than by using just either one of them. The other possible reason for the lower accuracy in place B is that we used time series remote sensing images; with the fragmented land cover types, it is difficult to identify grassland. However, another possible reason for the better performance in place A is that it's easy to choose training data because of the regularly distributed land use types (Figure 4.1). Furthermore, the overall accuracy of place A and B also depends on the reference data. Comparing the results with the MCD12Q1 and the Mapbiomas product, we qualitatively observed that classification results are closer to the Mapbiomas product, which is the 30 m by 30 m classification product. This also indicates that the proposed model can improve performance of remote sensing image processing, in either a regular land use distribution area or a fragmented land use area.

Specifically, the results indicate that different land use types have different performances in places A and B. The reason for the higher accuracy of cropland is that the places we chose have been experiencing continuous agricultural expansion, which makes it easier to collect training data. For example, the south in place A is partially in the western of the state of Bahia, and this area is the main crops areas of this state (Araújo et al., 2019; Noojipady et al., 2017). In place B, the accuracy of cropland is slightly higher than place A because the cropland is randomly located in the study area. September is still at fallow period, the SAVI, which considered soil background can improve the performance of cropland pixels that mixed with other land cover types. da Silva et al., (2020) also used SAVI to remove soil background influence to improve their classification result. On the other hand, the grassland has the lowest accuracy in place B and the reason is that the study area is a subtropical savanna, and forestland in this area means there are trees, but they cannot form a canopy (Schwieder et al., 2016). With the mixed grassland and forest, the reflectance bias could cause the error. Additionally, in this study, the main goal is to classify cropland, grassland, and forestland. However, there are also bodies of water and urban areas in both places, which occupy very few pixels. Because we used the MODIS product with a spatial resolution of 478 m, we just ignored them and treated them as grassland, which is the other possible reason causing the lower overall accuracy in place B.

4.4.3 The relationship between agricultural expansion and burned area

Recently, with the cheap land price and government encouragement, the Matopiba region has become the new agricultural frontier and more than 50% of the natural vegetation has been converted into cropland, especially in the western region of the state of Bahia and the central of the Matopiba region (Araújo et al., 2019; Spera et al., 2016). To estimate the interaction between fire activities and agricultural expansion, we overlaid these two maps. Our results indicate that most burned areas occurred in the grassland in place A and forestland at place B. The possible explanation could be the heterogeneity of the landscape. Grassland is concentrated on the left side of place A, and grassland is the most common land use to apply fire activity (Pivello, 2011; Rodrigues et al., 2019). Moreover, the possible reason of burned areas in forestland at place B could be that forestland is the dominant land use in this place; it is mixed with grass and trees, and farmers prefer to burn grass to prepare for the crop-growing season (de Araújo et al., 2012; Pereira et al., 2017). Besides, this region has a two-season climate, and September usually is the last dry season month. Farmers need to prepare land for the growing season and most of them chose to burn residues on the land especially for the large-scale farms.

Furthermore, the reasonable explanation for burned areas occurring at the edge of cropland in both places (Figure 5.4) is that this region is experiencing agriculture expansion. Recently, though some studies conclude that agricultural expansion in the Cerrado is the result of agricultural intensification, in this new agricultural frontier, agricultural expansion still keeps agricultural extensification during the study period (Martinelli et al., 2010; Rada, 2013). The estimation further evidence that agricultural expansion in this region is an ongoing phenomenon that could affect the environment.

4.5 Conclusion

Deep learning algorithms have been broadly used in the remote sensing community to improve classification performance. This paper proposed a novel deep learning model to classify time series remote sensing images and we estimate the interaction between classification results and burned areas. The proposed model can consider the spatial and temporal resolution of the remote sensing at the same time, which provides a novel way to classify multispectral remote sensing images. The classification results also increased evidence that the proposed model is stable when applied to different land use and land cover areas. Second, we applied the proposed model with the MODIS remote sensing image in two places in the Matopiba region, which filled a gap that deep learning model can also classify coarse spatial resolution images. Finally, the overlaid analysis of classification results and burned areas also provides a feasible way to investigate internal relationships between fire activities and the environment in a particular month.

Our results showed that we achieved a more than 75% overall accuracy of two places using the proposed model with the MCD12Q1 V6 annual land use and land cover map as reference data. The overlaid analysis with burned areas indicated that burned areas easily happened in the grassland at place A and forestland at place B. However, there are still some limitations in this study. First, we used the MODIS MCD43A4 V6 reflectance product to apply to the proposed model, which has very coarse spatial resolution, and one single pixel could mix different land use types. This unavoidable drawback exists in many remote sensing images and it could affect the performance of the model. Second, the patched based method is a reliable method for classifying remote sensing images using a deep learning algorithm such as CNN and RNN. But due to the complexity of the land surface object, it is difficult to choose an optimal size of patch. The size of the patch depends on the spatial structure of land use and land cover type, and some studies used finer size to classify remote sensing images (Ndikumana et al., 2018; Sharma et al., 2018). However, in this study, the areas we chose are simple; they are dominated by cropland, grassland, and forestland, and we chose each patch size as 15*15, with the model already giving us decent results. However, in the future we would like to try a finer patch size to remove classification errors. Finally, as we known, deep learning models require very expensive computer calculation capability. In this study, we collected remote sensing images for the same day in different years to fit the proposed model. However, in the future when more advanced hardware is available, we would like to try to apply the model a shorter duration in order to improve the performance. Nevertheless, this study still provides an advanced deep learning algorithm to classify land use over time and the proposed method can apply to other places when considering spatial and temporal scale.

Acknowledgements

The authors would thank the Land Processes Distributed Active Archive Center (LP DAAC) for providing MODIS land products free of charge. We are thankful for the help from the KDD lab in Computer Science department. We also thank the anonymous reviewers who provided helpful comments on the manuscript.

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Chapter 5 - Conclusion

Currently, with the development of the computer science and remote sensing communities, more advanced methods, combining these two fields are being used to estimate the interaction between agricultural expansion and the environment. For example, compared with traditional statistical methods, machine learning methods can achieve a better performance in classification and regression problems (Ali et al., 2015; Luo et al., 2019; Sharma et al., 2017; C. Zhang et al., 2019). Moreover, in this era of big data, social media data has been introduced into the geographic field to analyze disaster management and climate change research (Batrinca and Treleaven, 2014; Pacifici et al., 2015; Resch et al., 2018; Roxburgh et al., 2019). In my dissertation, the core idea was to apply these advanced methods to estimate the interaction between agricultural expansion and the environment from spatial and temporal scales.

My dissertation research focused on three questions derived from the one big problem that the interaction between agricultural expansion and the environment. In particular, I investigated the spatial distribution of pollinator and soybean production in different periods, its environmental vulnerability because of agricultural expansion in different years, and the correlation between agricultural expansion and burned area caused by fire activities in different places. To discuss all these questions, I used remote sensing imagery, GIScience, model approaches, machine learning algorithms, and data mining methods. The results for each question showed that machine learning is a reliable method for analyzing the interaction between agricultural expansion and the environment at a regional scale, and remote sensing imagery is a cost-effective data resource to analyze regional problems corresponding with human activities. Here I summarize my findings and provide suggestions for on-going research.

5.1 Pollinator, agricultural expansion and environment

The interaction among pollinators, crops, and environment is the biggest problem for developing agriculture. In Chapter 2, I presented model approaches to estimate the spatial distribution of bees' richness and soybean production and discussed their potential interaction. To connect environmental variables that affect bee species and soybean output during the growing season, I chose a species distribution model, which used climatic variables and bee occurrence data to predict bees' richness for two different periods and the WOFOST model was used to simulate soybean production corresponding with environmental variables for selected years. After validating the soybean production results, I concluded that the WOFOST model was a reliable crop simulation model to estimate soybean production using remote sensing data in the Brazilian Cerrado, and my results showed higher soybean production distributed in the southern Cerrado. Moreover, many studies have concluded that the species distribution model is a robust method for modeling species distribution (Elith and Leathwick, 2009; Galv et al., 2017). Different from these studies, I stacked a species distribution model to predict bee species richness based on existing literature (Distler et al., 2015; Guisan and Rahbek, 2011), and my results indicated that high bee species richness was also in the southern Cerrado during the study period. Analyzing these two results, I concluded that bee species richness had a stronger response to environmental changes compared with soybean.

After generating the maps of bee species distribution for two periods and three selected years of soybean production, I did a correlation analysis by overlaying these results. My analysis indicated that the spatial interaction between bee's species richness and soybean production had a nonlinear relationship. The result captured that with bee species richness, soybean output increased, but soybean production also increased when richness was low. However, it was interesting to note that when richness was high, soybean production decreased even when bee species richness continued to increase. This result revealed that there were other factors affecting soybean production such as agricultural technology and climate variables (Martinelli et al., 2010; Rada, 2013). These findings provided insights into the spatial distribution between pollinator and soybean production, and the potential that correlation analysis might help researchers to understand their interaction at a regional scale.

5.2 Environmental vulnerability in the Cerrado

The consequences for agricultural expansion include soil erosion, vegetation health, and land degradation. Environmental vulnerability is an alternative method for understanding environmental responses due to agricultural expansion. In Chapter 3, I estimated environmental vulnerability in the Brazilian Cerrado using remote sensing image, machine learning algorithm and Twitter data. There were many factors potentially affecting environmental vulnerability in this region; I focused on the natural environment, which included climate variables and natural vegetation. Based on the definition of environmental vulnerability provided from the IPCC, I selected five exposure variables and six sensitivity variables. Then I created an Autoencoder model that is one type of machine learning method to generate the optimal exposure indicator and sensitivity indicator, respectively. The results showed that the machine learning algorithm was feasible in the environmental assessment field, and the study expanded the evidence of the application of the method (Javadi et al., 2017). Next, I applied the Displaced Ideal (DI) method to estimate environmental vulnerability in the Cerrado for 2011 and 2016. The results showed that the high environmental vulnerability areas were in the southern Cerrado, and low environmental vulnerability areas were in the northern Cerrado. Moreover, compared to the period from 2011 to 2016, some agricultural states such as Mato Grosso, Mato Grosso do Sul, and Góias had environmental vulnerability rates slightly changing from medium to high, which means that agricultural expansion could be one major factor causing vulnerability change.

One main problem about environmental vulnerability assessment is how to validate the result, especially estimating historical environmental vulnerability. In this chapter, I used historical Twitter data to validate the results of the model. Currently social media data has become a promising dataset in the science field and many studies have pointed out its value in the academic world (Batrinca and Treleaven, 2014; Resch et al., 2018). I mined historical tweets from 2011 and 2016 (from January 1th to December 31th) to collect vulnerability related tweets, and my results showed that more than 80% of tweets were related to high environmental vulnerability, which matched my modeled results.

Combining machine learning algorithms and Twitter data to estimate environmental vulnerability is a novel idea and my results indicate that they are good enough for estimating vulnerability at a regional scale. However, because of the limitation of the historical Twitter dataset, the research required more evidence to improve the current result. Nevertheless, these findings are important for providing alternative methods in the environmental vulnerability assessment field.

5.3 Deep learning, agriculture, and fire activity

Deep learning has been broadly used in the remote sensing community to interpret remote sensing images. Many of them focused only on benchmark data sets, but their results showed that the performance is better than traditional machine learning algorithms (Paoletti et al., 2018; Yu et al., 2017; Zhang et al., 2018). In Chapter 4, I created a novel Conv-LSTM deep learning model using Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) to classify time serial MODIS remote sensing images in two agricultural expansion sites in the Matopiba region and estimated the correlation of each land use type with burned areas caused by fire activities in September.

Results indicated that the overall accuracy in both sites were higher than 75% when compared with MCD12Q1A V6 annual land use and land cover MODIS products. Meanwhile, I also visually compared results with the Mapbiomas product, and analysis results indicated that the proposed model was robust in classifying coarse spatial resolution time series remote sensing images with different land use structures. The highest overall accuracy in site A was grassland, and the lowest overall accuracy was cropland. However, in site B, the highest overall accuracy was forestland and the lowest one was grassland. The different land use type performance revealed that there are many different factors that affect the classification task, such as spatial resolution, growing season and cloud problems. Excepting these limitations, the proposed model was reliable for classifying time series remote sensing images.

Because September is the last month of the dry season in this region, fire activities happen more in September than in other months (de Araújo et al., 2012; Pereira et al., 2017). To understand how fire activities might affect each land use type in both sites, I also collected burned area maps for this month from the MCD64A V6 MODIS product to estimate its correlation with each land use type using classification results. It indicated that the most burned areas happened in grassland at the site A, and forestland at the site B. These findings provided insights that may help local governments with environmental management. In terms of where fire activities happen occurred, it also found that many burned areas were at the edge of cropland, which suggested that farmers were using this way to expand agriculture in this region. However, more evidence is needed in the future to fully understand the interaction between fire activity and agricultural expansion.

5.4 Limitation and Further Direction

With the development of remote sensing and geographic information system, applying them together to analyze the interaction between agricultural expansion and environmental impacts has become a major approach, which can provide spatial and temporal insights to problems. Furthermore, integrating advanced methods such as machine learning and new data types such as social media data can improve estimate accuracy. Although my results provided evidence that these methods are reliable at the regional scale, there are still some limitations and uncertainties.

First, remote sensing imagery is a cost-effective choice for my dissertation. There are different spatial and temporal resolution. In the dissertation, due to the size of the study area, I chose coarse spatial resolution remote sensing images for all chapters. One advantage of coarse spatial resolution remote sensing images is that it has a short revisit time, which can provide more data for the proposed models. But the drawback is we cannot read details for the particular location. For example, in Chapter 2, I used a spatial resolution of 25 km by 25 km climate variables to model bee species richness and soybean production. Although the results were interesting, it was difficult to generate detailed information in a particular place. In Chapter 3, I used a spatial resolution of 10 km by 10 km to match the Twitter data, and my results were useful for local governments to build a sustainable environment, but the spatial resolution is still coarse. In addition, many remote sensing images have cloud cover problems, especially during the wet season in the study areas, which could affect the final result. For instance, in Chapter 4, I downloaded the adjusted remote sensing images, but there are still some potential cloud cover problems. In the future, I will try more advanced methods to remove cloud noise in the remote sensing image or use finer spatial resolution of remote sensing images.

Second, in the dissertation, I used traditional machine learning algorithms such as Support Vector Machine, Random Forest, and deep learning algorithms such as Convolutional Neural Network and Long Short-Term Memory. Machine learning as a novel alternative has been widely used in the remote sensing community. My results indicate that it is also a promising application for estimating the interaction between agricultural expansion and its impacts on the environment. The most important reason to use machine learning is the quality of input data, which strongly depends on the final result. For example, in Chapter 2, I collected bee occurrence data from online sources, and they were limited to just numbers of selected species after clearing the raw data. This insufficient data set could potentially affect model results because of the data limitation.

Finally, in Chapter 3, I used Twitter data in my dissertation to validate environmental vulnerability. Social media data is useful in the academic field, but my work is the first time it has been used in the environmental assessment field. Though it provides us useful information to understand environmental systems, it still has some limitations. For example, the volume of historical tweets is way less than streaming twitter data, which could increase the bias of results. Second, Twitter data is heavily dependent on the geographic location where higher population density areas could have more people using the platform. In the future, I will try more advanced methods to improve the assessment.

Additionally, this dissertation focused on the estimates of interaction between agricultural expansion and the environment from spatial and temporal scales. I addressed the problem of the Brazilian Cerrado, which is a typical subtropical savanna region. The findings provide useful evidence to guide expanding agriculture at a regional scale and proposed methods are robust to duplicate these methodologies in other regions.

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Appendix A: supplemental data and code source

There are explanations about supplemental data for each Chapter in this dissertation. In Chapter 2, I had 16 selected bee occurrence datasets, and some environmental variables. In Chapter 3, I had environmental variables and historical Twitter data. In Chapter 4, I had MODIS products. Beyond these datasets, I also used computer programming to generate the results.

I will divide them into four types:

1. Bee occurrence data. You can find the selected bee occurrence data from:
   https://doi.org/10.1016/j.scitotenv.2020.139674
2. Environmental variables that were collected from remote sensing images:
   Goddard Earth Sciences Data and Information Services Center (GES DICS)
   Tropical Rainfall Measuring Mission program
   MODIS product: https://lpdaac.usgs.gov/
   Historical Twitter data: Twitter data API
3. Code resource:
   Models in Chapter 2: WOFOST model (https://pcse.readthedocs.io/en/stable/), and
   SSDM (https://cran.r-project.org/web/packages/SSDM/SSDM.pdf)
   For other Code, you can find them on my Github page: https://github.com/lwind18